

# Academic Entrepreneurship: Entrepreneurial Advisors and Their Advisees' Outcomes

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**Abstract.** The transfer of complex knowledge and skills is difficult, often requiring intensive interaction and extensive periods of coworking between a mentor and mentee, which is particularly true in apprenticeship-like settings and on-the-job training. This paper studies a context that quintessentially describes this type of learning: the academic laboratory. I focus on ways a change in the attention of a principal investigator, moving to entrepreneurship, may influence knowledge transmission and skill development by examining the relationship of this change with their PhD students' scientific productivity and careers. To do so, I rely on novel restricted-access data encompassing faculty and PhD students in computer sciences, engineering, and the life sciences who were active at an elite U.S. research university from 2001 to 2017. The results suggest a substantial negative association between a professor's entrepreneurial activity and the short- and long-run publication output of the PhD students they train. Furthermore, I detect a decrease in students' likelihood of becoming professors themselves but an increase in their likelihood of working for consulting firms on graduation. Finally, I provide evidence suggesting that changes in trainee development are the most feasible drivers of the results rather than changes in trainee research orientation, selection, or life cycle effects.

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## 1. Introduction

Over the last decades, advanced economies have been increasingly shifting toward a “knowledge-based economy,” which entails greater dependence on cutting-edge knowledge, information, and high skill levels (Powell and Snellman 2004). However, the transmission of complex knowledge and skills from one actor to another can be a difficult and costly endeavor. It often requires face-to-face interaction, working side-by-side, and years of coworking between a mentor and mentee. This is particularly true in apprenticeship-like settings and on-the-job training, which together represent the vast majority of skill-based learning in the United States (Knoke and Kalleberg 1994, BLS 2021).

A setting that quintessentially describes this type of learning is the academic laboratory, which serves the fundamental roles of both producing knowledge and training future high-skilled knowledge workers.<sup>1</sup> These labs are spearheaded by faculty (principal investigators, hereinafter referred to as PIs and used

interchangeably with the term professor) who are responsible for running a laboratory that creates new knowledge in the form of publications (and potentially patents) and for training graduate students to become independent researchers (Stephan 2012). Both these roles tend to go hand in hand, where the majority of laboratory members are represented by PhD students who are being trained on the job and conduct most of the bench-work (Conti and Liu, 2015, Graddy-Reed et al. 2018, Chang et al. 2019).<sup>2</sup>

However, besides producing knowledge for the public domain and training the next generation of knowledge workers,<sup>3</sup> PIs have also increasingly become more proactive in their efforts to commercialize scientific discoveries (Mowery et al. 2004, Hsu et al. 2007, Crespi et al. 2011) stretching traditional academic boundaries to include entrepreneurial activities (Fini and Lacetera 2010). This comes in response to opportunities, organizational changes, and policy initiatives. Yet, results from both surveys and empirical studies that have

examined the potential ramifications of academics' engagement in commercialization are mixed (Agrawal and Henderson 2002, Murray and Stern 2007, Fabrizio and Di Minin 2008, Crespi et al. 2011, Thursby and Thursby 2011) and focus primarily on those engaging in these efforts, that is, the professors, and consequences for their own productivity.

In this study, I shift the focus of attention toward actors that depend heavily on PIs for access to complex knowledge and the development of skills: the PhD students that PIs train. Using the transition into academic entrepreneurship to capture changes in the attention and research orientation of PIs, I examine the potential consequences for PhD students. Specifically I examine how, on average, PIs' engagement in entrepreneurship, measured by the disclosure of entrepreneurial activity to their employer, may influence the innovative output and career trajectories of their PhD students. To do so, I track professors and their advisees at a top-ranked U.S. research university from 2001 to 2017, assessing variation in student outcomes in the cohorts before and after research faculty transitions into entrepreneurship. I focus my analyses on the fields of computer sciences, life sciences, and engineering, which are particularly important to examine given that (a) the bulk of academic entrepreneurs emanate from these fields, and (b) generally, PIs assume a very involved role as directors of their labs, although there are important field differences. Furthermore, using founders from these fields allows me to hone in on ventures based on technologies developed in scientific labs.<sup>4</sup>

The data underlying this study come from a host of sources consisting of both restricted administrative and publicly available information. They encompass, among others, information on professors' demographics, the number and quality of professors' publications, and information on their patenting output and the number of startups they establish. I complement these data by matching professors to their PhD students, based on information provided by the Office of Enrollment at the examined institution. For PhD students, I have access to detailed demographic and educational information and to PhD exit survey responses recording students' evaluations of their respective PIs. I additionally collect data on students' careers before and after graduation and on their publications, patents, and respective citations. To gain a better understanding of the idiosyncrasies of the examined institution and to guide my approach of teasing out potential mechanisms, I complemented my archival data collection effort with more than 20 hours of interviews with faculty, students, and staff.

Overall, my main findings provide suggestive evidence that working in a laboratory with an entrepreneurial PI, a

professor listed as a member of the founding team of a company, is associated with a considerable decrease in the number and quality of publications a PhD student produces both during the PhD program and afterward. Conversely, having an entrepreneurial PI does not seem to be significantly correlated with students' patenting output. Although these findings are plausibly the result of working under the supervision of an entrepreneurial PI, other alternative explanations are feasible. For one, it is possible that my results are driven by omitted variables, such as professor, laboratory-specific, technology, or life cycle trends. For another, selection, as manifested by changes to the composition of incoming PhD cohorts, may be driving my results.

I attend to these concerns, as far as possible, following a step-by-step approach and using a host of different controls and estimation techniques. I apply professor fixed effects to my estimation models, control for professor-year, age, and tenure-related trends, and estimate a coarsened exact matching (CEM) approach where I match students based on the characteristics of their advisors at entry into the PhD program. Furthermore, to assess what factors determine having an entrepreneurial PI, I implement a "double" LASSO machine-learning algorithm, which can be used to assess and address selection bias (Belloni et al. 2014b, Conti and Guzman 2019). I apply a first LASSO selection procedure to determine what factors predict student-advisor matches and a second LASSO to retain the largest explanatory variables of student performance. In addition, I provide evidence that the composition of incoming students does not appear to be shifting as a function of a PI's entrepreneurial activity. Finally, I estimate a difference-in-differences type panel model that includes student fixed effects to analyze within student changes year by year once exposed. The results across all models are consistent.

I further examine the implications of working under the supervision of an entrepreneurial PI for PhDs' long-term productivity and careers. Notably, the negative relationship with publication output that I find during the PhD program persists. I also detect changes in PhDs' career trajectories. The results suggest that PhD students exposed to an entrepreneurial advisor are less likely to ever become professors themselves and if they pursue the private-sector career route upon graduation, they are less likely to join a small firm and more likely to join a consulting firm.

To shed light on what may be driving my results, I examine two main potential mechanisms: 1) changes in PI attention toward entrepreneurship may shift PhD students' research orientation away from traditional academic output, and 2) as PIs' attention shifts

to entrepreneurship there may be changes in the level of training and mentorship students receive. My analyses reveal that the latter is more likely to serve as an explanation for my findings. In particular, I unveil decreases in both the level of advisor-advisee co-production and students' amount of first-authored publications. Moreover, I detect a reduction in the perceived quality of a PI's overall mentorship and availability scores and find suggestive evidence for a negative relationship between supervision by an entrepreneurial PI and students' likelihood of recommending the PhD program. Exploiting heterogeneity among students, I provide further support for the interpretation that there may be a decrease in student development rather than shifts in research orientation.

Taken together, although primarily correlational, my results provide fundamental insights for skill-based learning and apprenticeship-like training, which are critical for a knowledge-based economy. I focus my attention on the case of PIs whose tasks include the development of next generation knowledge workers. The findings highlight that a change in PIs attention, moving to entrepreneurship, can have far-reaching implications for fulfilling this responsibility.

This study is not without limitations, making it difficult to interpret my findings as causal. One feature of my study, but also potential limitation, is that I focus my attention on examining what happens when advisors become entrepreneurial in the first place rather than more entrepreneurial over time. As such, my findings can provide most insight on the extensive but less on the intensive margin of entrepreneurial activity.

## 2. Background

The knowledge-based economy hinges critically on high skilled human capital, an abundance of information, and cutting-edge technologies (Powell and Snellman 2004). However, the transmission of complex knowledge and skills is difficult and costly often requiring intense spouts of interpersonal information exchange and extensive coworking, which can sometimes entail years of mentees and advisees working side-by-side. This is particularly true in apprenticeship-like settings and on-the-job training that represent the vast majority of skill-based learning in the United States (BLS 2021, Fuller et al. 2022).

One context that provides a suitable setting to examine this type of learning is the academic laboratory. A long-standing stream of literature has provided evidence for the impact of the inventive output from academic research on productivity growth in the economy and its role for stimulating greater private-sector research and development (R&D) through knowledge spillovers (Jaffe 1986, Shane 2004, Audretsch et al. 2006, Lach and Schankerman 2008, Arora et al. 2020). One

important channel through which inventive output from academia is transferred to the public domain is via publications (Sauermann and Stephan 2013, Marx and Fuegi 2020). Another channel is through students educated at universities who receive training that fosters science-based problem-solving capabilities and who, as a consequence of such training, themselves become carriers of advanced knowledge (Graddy-Reed et al. 2018, Kaiser et al. 2018).

However, over the last decades, academia has been undergoing important changes, one of which entails an expansion of its traditional scope to include more commercially oriented channels, such as patents and new ventures, which have increased dramatically in number ever since (Acs and Audretsch 1990, AUTM 2017). Commercialization follows a distinct institutional logic and set of norms (Sauermann and Stephan 2013), and there are different types and levels of involvement ranging from patenting to entrepreneurship, where the latter requires the most commitment.<sup>5</sup>

To date, most research examining faculty engagement in commercialization has focused on understanding why professors get involved in commercial activity (D'Este and Perkmann 2011), the characteristics of those professors who do (Agrawal and Henderson 2002), and what the implications of commercialization are for professors' time, knowledge, norms, and resources (Shibayama et al. 2012). This body of literature points out that the participation of academic professors in commercial activity is partially a response to university organizational mechanisms and public policies that shape incentives (Lach and Schankerman 2004, Mowery et al. 2004, Toole and Czarnitzki 2010), as well as other individual-level motives (Cohen et al. 2020). Moreover, the empirical evidence suggests that the most productive academic life scientists are those involved in commercialization (Agrawal and Henderson 2002). Specifically in the case of biotechnology, an influential stream of research points to the fundamental role "star" scientists play in transferring new academic knowledge to industry (Zucker et al. 1998, 2002; Toole and Czarnitzki 2009; Higgins et al. 2011).

Extant research has investigated the impact of the adoption of commercial attitudes and behaviors by academic researchers on a number of outcomes (Louis et al. 1989, Dasgupta and David 1994, Powell and Owen-Smith 1998, Etzkowitz 2003, Stuart and Ding 2006, Stephan 2012). These include changes in behaviors of researchers, such as regarding sharing scientific resources (Shibayama et al. 2012), as well as shifts in the amount, direction, and quality of scientific research. Some express concerns about commercial engagement of academic scientists and its potentially detrimental impact on academic research. The perceived risks include a shift in the content of scientific

research toward more applied topics (Blumenthal et al. 1986, Behrens and Gray 2001), a slowing-down of open knowledge diffusion (Nelson 2004, Murray and Stern 2007), or even an exodus of academic scientists to industry (Azoulay et al. 2009). Because faculty participation is critical for successful commercialization, this may also incur significant costs straining professors' available time, energy, and other resources (Zucker et al. 1998, Jensen and Thursby 2001, Lach and Schankerman 2004, Shane 2004, Agrawal et al. 2006). Others are less concerned, finding that commercialization may enhance traditional scholarship (Goldfarb et al. 2009, Shichijo et al. 2015) and does not seem to detract from university knowledge production (Thursby and Thursby 2007, Abramo et al. 2012).

Thus far, debates on academic commercialization have predominately focused on consequences for their own productivity or open science (Bhaskarabhatla and Hegde 2014) but have largely left the potential ramifications for PhD student training, which takes place in academic labs spear-headed by faculty, unexplored. Training, and thereby the transfer of specialized skills and knowledge, occurs over the course of years in an apprenticeship-like manner with the goal to ultimately produce independent researchers who themselves can produce new knowledge and pass complex information on to others. The development of PhD students has both important implications for the advancement of science in general and for private-sector innovative output. On the one hand, the expectation is that some of these individuals graduate to become PIs themselves, eventually leading their own labs and contributing to basic and applied knowledge and the overall production of science (Graddy-Reed et al. 2018). On the other hand, for those that do not take the academic career route, their training as university research scientists, which fosters science-based problem-solving capabilities, may be crucial for private sector firms' innovative output (Kaiser et al. 2018).

Ex ante, it is not clear what the impact of faculty engagement in entrepreneurship is on their PhD students. Following extant research there are both possible advantages and disadvantages that could be associated with being advised by an entrepreneurial PI. The directionality of the overall relationship will depend on what occurs when students' research endeavors and their advisors' entrepreneurial activity meet and when the educational and entrepreneurial mission meet. PIs' engagement in entrepreneurship could influence both students' research orientation, as well as the level of engagement PIs (can) devote to the development of their advisees to independent researchers.

Possible advantages of working under the supervision of an entrepreneurial PI could be that students receive more commercially oriented training, which

may strengthen students' future ability to commercialize knowledge, to create more useful research and to achieve better career prospects in entrepreneurship and industry (Fabrizio and Di Minin 2008, Franzoni 2009, Goldfarb et al. 2009, Perkmann et al. 2013). Given the current oversupply of PhDs in certain fields, this may present an important avenue in shifting labor supply to more appropriately mirror labor demand creating new opportunities for faculty and students (Stephan 2012). If this is the case, we should detect a higher likelihood of a student entering into industry and/or better placement and could potentially observe an increase in the amount and quality of commercially oriented output that students produce.

Possible disadvantages of working under the supervision of an entrepreneurial PI could be that students receive less attention given the potential distraction of advisors with their new task (Hellmann 2007). As pointed out by Powell and Owen-Smith (1998), entrepreneurial engagement could weaken the traditional research and education mission of professors, thereby negatively impacting the academic training and mentoring students receive. It is also feasible that engagement in entrepreneurship entails fundamental changes in the usefulness of research emanating from a PI's laboratory for the academic research community (Murray and Stern 2007). As a consequence, we should then observe a decrease in the amount and quality of academically oriented output that students produce during the PhD program and after as well as poorer career outcomes within academia.

Naturally, it is also possible that a PI's engagement in entrepreneurship does not affect the PhD students they train. The additional task of starting a company may not take away resources that would have been spent training students (Thursby and Thursby 2007) or change professors' direction or quality of research and commitment to their labs (Azoulay et al. 2009, Goldfarb et al. 2009). If this is the case, then we should detect a null correlation between entrepreneurial activity and the output produced by PhD students as well as subsequent career outcomes.

### 3. Data Construction, Descriptive Statistics, and Patterns

To understand the relationship between changes in PIs' attention and research orientation brought about through a transition into entrepreneurship and student outcomes, I compiled a unique data set using rich administrative information from various sources. The core information on the sample underlying this study is based on confidential data provided to me by the research university examined. The research design was approved by the university's institutional review

board (IRB). The records of all subjects were anonymized prior to analysis.

For the purpose of this study, I focus on the colleges of Computer Sciences, Life Sciences, and Engineering covering a total of nine distinct departments and 24 majors. The departments are aerospace engineering (AERO), biomedical engineering (BIOMED), chemistry (CHEM), chemical and biomolecular engineering (CHEME), civil engineering (CIVIL), electrical and computer engineering (ECE), computer sciences (CS), mechanical engineering (ME), and materials science and engineering (MATERIALS). Four reasons why I select these areas are (a) to avoid introducing field-specific biases (Perkmann et al. 2013) and to exploit field differences (Cohen et al. 2020), (b) because these areas produce the majority of doctoral recipients (with the strongest upward growth trend; National Science Board 2018), (c) most entrepreneurial activity that is based on scientific discoveries and is research-intensive originates from these fields (Agrawal and Henderson 2002, Goldfarb et al. 2009), and (d) PI's play a particularly important directive role in the production of science.<sup>6</sup>

The research university I examine is among the leading research universities and public colleges in the United States (National Science Foundation 2018). Every year, the R1 university provides education to more than 25,000 undergraduate and graduate students in fields ranging from engineering, computing, and sciences to business, design, and liberal arts. Given its high standing as an innovative top research institution, this school is a likely destination for students who want to be research active. Within the university and among the different colleges, there is some variation in terms of department quality. Most, however, are among the leading departments in their field worldwide. Program rankings of the departments included in my sample vary from number one to top 20 in the nation.<sup>7</sup>

In what follows, I will describe the precise data sources accessed to construct my data set and the extent of coverage I was able to attain. I base my sample of professors from information provided to me by the Office of Faculty Affairs. The initial sample consists of 1,053 professors who were faculty at the focal research university between 2001 and 2017. For all these professors, I have access to detailed demographic information including age, nationality, gender, ethnicity, and department affiliations and time of achieving tenure milestones. In addition, I collect data on professors' publication output from Scopus (scopus.com) and retrieve information on patenting from the United States Patent and Trademark Office Patentsview Patent Database (patentsview.org). I do so using names, biographical information, and affiliations to identify each professor's ID on Scopus and the Patentsview Patent Database.<sup>8</sup> Details on the

entrepreneurial activity of professors was provided by the university's business outreach organization.<sup>9</sup> In this paper, professors are considered entrepreneurial starting the year the startup they are listed on as a founding team member is established. This date is based on the first funding round and implies a level of seriousness of founding intent. Given conflict of interest reporting, professors are expected to report all such activity to the university.

### 3.1. Professor-Level Descriptive Statistics and Productivity Patterns

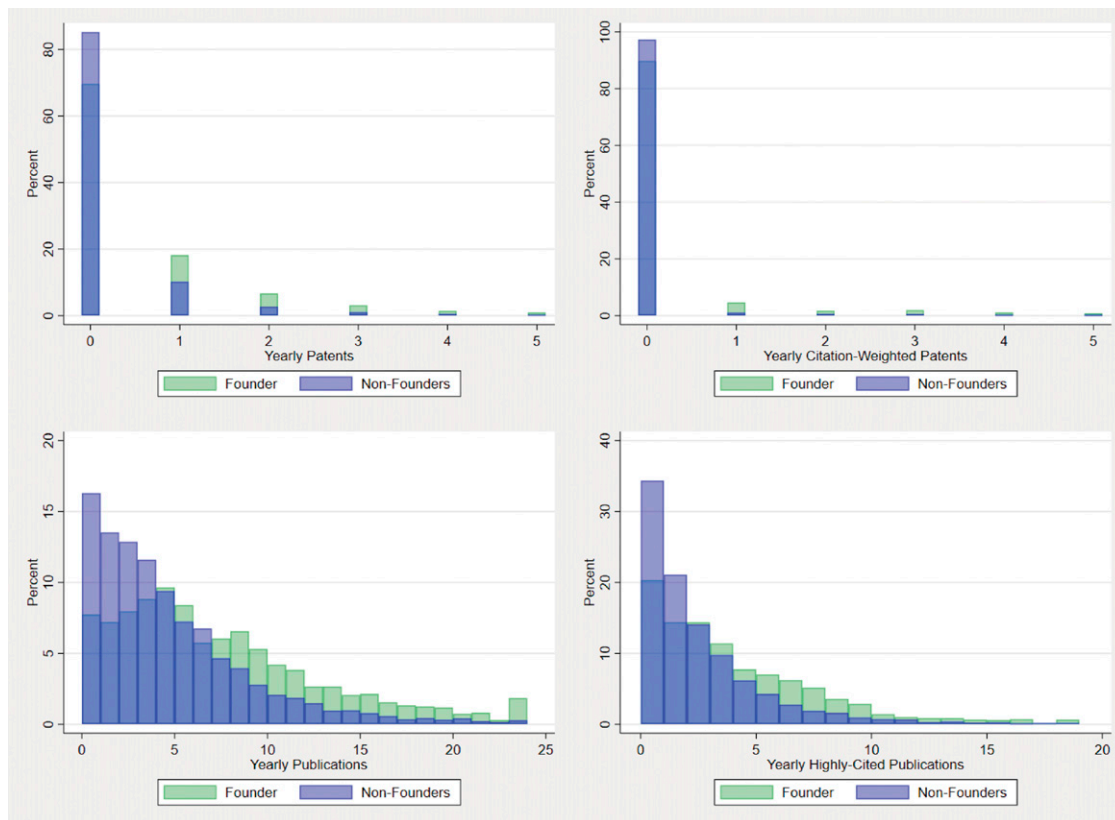
In Figure 1, I display the innovative output of professors at the research institute I examine, contrasting entrepreneurial and nonentrepreneurial professors. The graphs present the distribution of professors' yearly patent and publication output. For presentation purposes, I cut off patent output at six yearly (citation-weighted) patents and 25 (highly cited) publications. As shown, entrepreneurial professors tend to produce more patents, publications, and highly cited publications and slightly more citation-weighted patents.<sup>10</sup>

Figure 2 depicts the number of faculty founders at the research university by year from 2001 through 2017. There is strong variation in the number of startups created in each year. Overall, there are 92 unique founders who founded 109 startups. To ensure that the time of entrepreneurship is indeed the most accurate, I triangulate using other data sources (year coverage is restricted) provided to me that link federal I-corps grants (federal grants provided by the National Science Foundation (NSF) for venture creation), patents, and incorporation to the establishment date I use as the time of startup. The average time between establishment and incorporation is half a year. As depicted in Figure 3, grant date and establishment tend to coincide, and as depicted in Figure 4, patent activity measured using the total amount (left) and citation-weighted number of patents (right) picks up starting in the two to three years prior to establishment. Previous studies suggest that academic patenting responds to changes in scientific opportunities, which could likewise be the case for engagement in entrepreneurship (Azoulay et al. 2007).

To obtain the results displayed in Figures 3 and 4, I estimate the following equation:

$$P_{p,d,t} = \alpha \text{FromFounding}_{p,t} + \text{Advisor}_{p,t} + f_p + f_{d,t} + \epsilon_{p,d,t}, \quad (1)$$

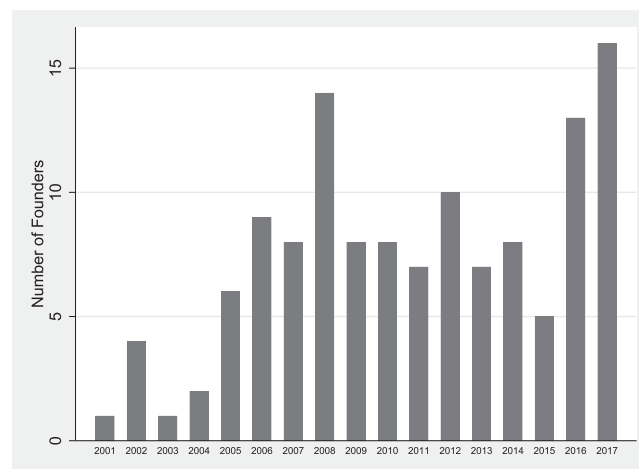
where  $f_p$  and  $f_{d,t}$  represent professor ( $p$ ) and department-year ( $d,t$ ) fixed effects, and  $\epsilon_{p,d,t}$  is the error term. Robust standard errors are clustered on the year level to account for intragroup correlation. I include these fixed effects provided that entrepreneurial professors

**Figure 1.** (Color online) Innovative Output of Professors: By Founder or Not

Notes. This figure displays the distribution of yearly patents (top) and publications (lower) produced by all nonfounder professors (darker shade) versus professor-founders (lighter shade). For presentation purposes, I cut off patent output at six yearly (citation-weighted) patents and 25 (highly cited) publications.

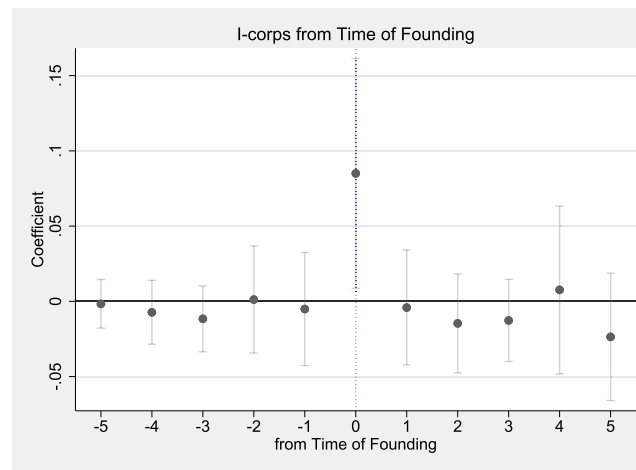
appear to be more productive on average (Figure 1) and to observe within professor differences depending on the time to or after founding a company ( $FromFounding_{p,t}$ ) while controlling for certain field trends. The outcome variable  $P_{p,d,t}$  refers to the respective output. In Figure 3 this corresponds to the

likelihood of receiving I-corps funding, and in Figure 4 this corresponds to the log transformed amount of patents  $(\ln(P_{p,d,t}+0.2))^{11}$  a professor  $p$  produces in a given year. I further include a control for whether the professor was an advisor in a given year ( $Advisor_{p,t}$ ).

**Figure 2.** Number of Founders by Year

Note. This figure depicts the amount of faculty founders (not unique founders) at the research university by year from 2001 to 2017.

**Figure 3.** (Color online) I-Corps Funding as a Function of Founding a Company

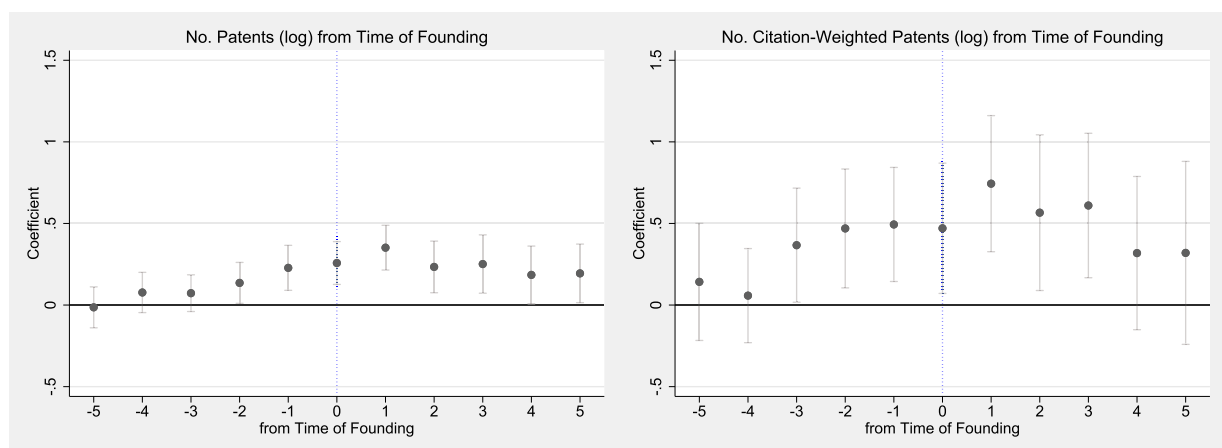


*Notes.* This figure displays the likelihood of receiving I-corps funding in relation to time from founding ( $x$  axis). All results are obtained controlling for a professor having at least one student and using professor and department-year fixed effects. The dashed vertical line indicates time of founding, and the confidence intervals displayed are at the 95% level. Robust standard errors are clustered on the department-year level.

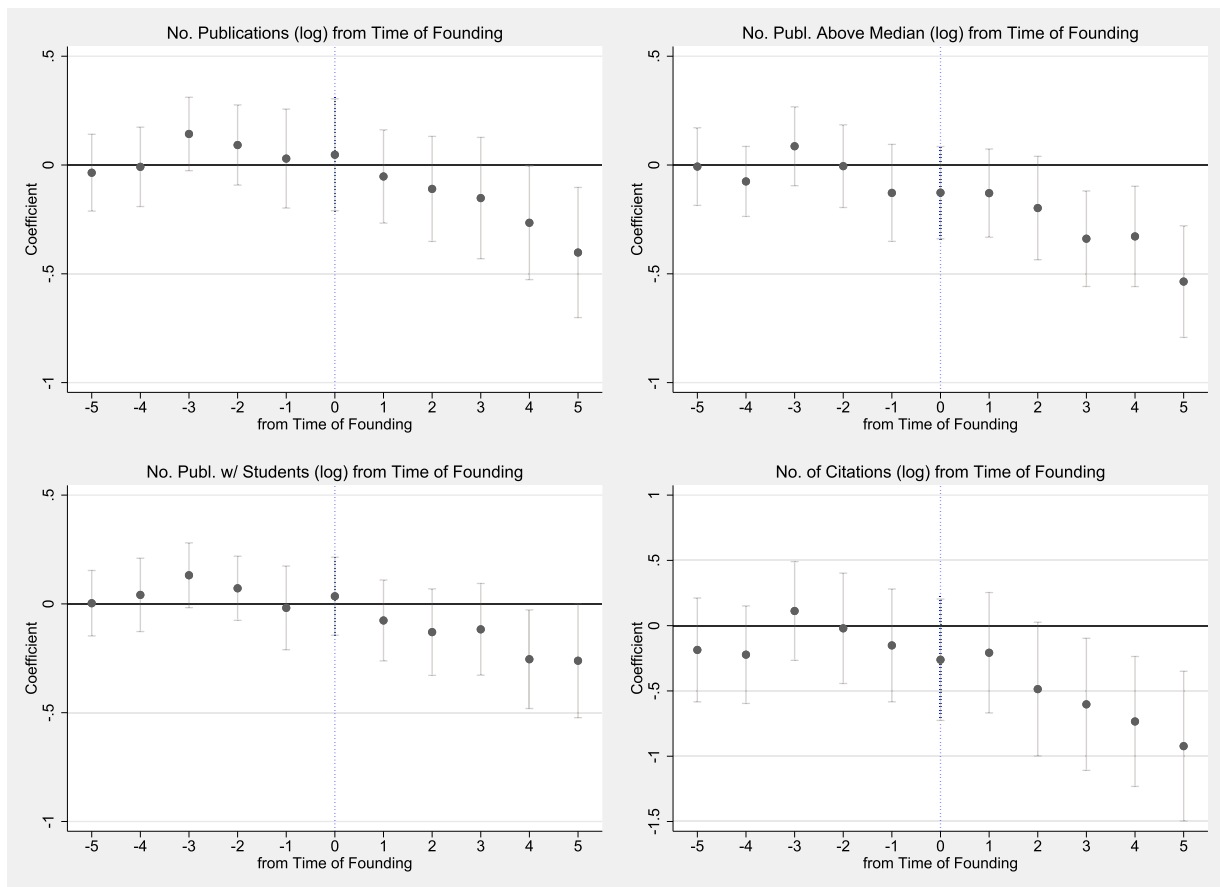
In Figure 5, I display the corresponding patterns for professors' publication output with relation to time from founding ( $x$  axis). To do so, I estimate Equation (1) using the total number of publications, the total number of highly cited publications, the number of publications coauthored with students, and the number of citations a professor has in a given year as measures for publication output (all log transformed as for patents). I further include a control for the log cumulative number of unique coauthors a PI has in a given year (the results are similar with or without inclusion of this variable). As depicted, entrepreneurial PIs' own relative publication productivity changes

as a function of transitioning into entrepreneurship several years after the transition. In the case of the total amount of publications, the drop becomes detectable five years and more after founding. For highly cited publications (with citations above the median) the figure displays a similar pattern. However, the drop becomes statistically significant three and more years after founding. The number of publications coauthored with students decreases in the fourth year and thereafter. Furthermore, I detect a drop in the number of citations a professor receives starting two years after founding, although the results are not statistically significant on conventional levels. Overall,

**Figure 4.** (Color online) Professor Patenting Activity as a Function of Founding a Company



*Notes.* This figure displays the relationship between founding ( $x$  axis indicates the time from startup year) and professors' patent output ( $y$  axis; all outcomes in log). The results are obtained controlling for whether the focal professor has at least one student and using professor and department-year fixed effects. Category 5 denotes all years five or more after founding date. The omitted category is six or more years prior to startup. The dashed vertical line indicates time of founding, and the confidence intervals displayed are at the 95% level. Robust standard errors are clustered on the department-year level.

**Figure 5.** (Color online) Professor Scientific Productivity as a Function of Time from Founding a Company

**Notes.** This figure displays the relationship between founding ( $x$  axis indicates the time from startup year) and professors' publication output ( $y$  axis; all outcomes in log). The results are obtained controlling for whether the focal professor has at least one student in a given year for the cumulative number of a professor's coauthors and using professor and department-year fixed effects. Category 5 denotes all years five or more after founding date. The omitted category is six or more years prior to startup. The dashed vertical line indicates time of founding, and the confidence intervals displayed are at the 95% level. Robust standard errors are clustered on the department-year level.

these patterns suggest that professors' yearly scientific productivity, as proxied with publication output, decreases by slightly more and slightly less than the move from the average to median professor's output per year starting five and three years after founding. As displayed in the online appendix, in Table A1, Panel A, when I change the omitted variable to year of founding, the results remain similar, although there is a perceivable bump in publication output three and two years prior to founding. These results are, however, not statistically significant on conventional levels. I further apply an alternative specification where I include a variable capturing the time from tenure (Panel B). Again, the results are similar.

### 3.2. Student-Level Descriptive Statistics

The base sample of PhD students was provided to me by the university's Office of Enrollment. For all these students, I have access to detailed demographic information including age, nationality, gender, ethnicity,

department affiliations, majors, year of admission, graduation, their prior degree-granting institutions, level and type of degree attainment, standardized test scores, and incoming grade point averages (GPAs). Based on the official advisor recorded at the Office of Enrollment, I match students to their advisors. As I proceeded with professors, I also collected information on each student's publication output including their pre-PhD publication record from Scopus (scopus.com),<sup>12</sup> and I retrieve data pertaining to patents from the USPTO Patentsview Patent Database (patentsview.org).<sup>13</sup> I additionally classify students' previous degree-granting institutions based on the World Academic Ranking of Universities (shanghaiacademicranking.com), and I denote a university as top tier if it is among the top 50 in a student's department of enrollment. To attain information on students' career outcomes, I retrieve students' curricula vitae from LinkedIn. For those who do not have a LinkedIn profile, I conduct extensive searches on the web using secondary sources such as university and company websites, publication and patent affiliations, CrunchBase, and

Bloomberg. The research university I examine further granted access to the PhD student exit survey that all students complete on graduation. This survey covers the graduation cohorts of 2012 to 2016 and includes information about funding sources, self-reported publications, and a student's evaluation of their main advisor.<sup>14</sup>

In Table 1, I report key descriptives for PhD students of entrepreneurial advisors only, encompassing a total of 647 students with 92 entrepreneurial professors.<sup>15</sup> Of these students, 63% work with a PI engaged in entrepreneurship during their PhD program ( $ePI (= 0/1) = 1$ ). The average length of exposure to an entrepreneurial PI ( $ePI$  (continuous)) is two years and goes up to a maximum of nine years. Twenty-two percent of the students are female, and 58% are Asian. I report the students' home department. Students' majors can transcend these departments, and there are many more (24 majors).<sup>16</sup> I further report the GPA and GRE scores at entry into the program. The variation in terms of GPAs is larger given that more than 60% of the students are foreigners, and GPAs outside of the United States do not correspond directly to those in the United States. Regarding the GRE scores, however, variation is more limited, with the median quantitative score being close to the maximum attainable score. Of the students in my sample, 21% had previously received a master's degree, 13% had received their previous degree from a top tier university (according to the World Academic Ranking of Universities found on shanghairanking.com, and I denote a university as high quality if it is among the top 50 in a student's field of enrollment), 19% had held a job, and 31% had at least one publication prior to the PhD. The range of students' publication and patenting output during the PhD program is wide, a reason why I log transform ( $\log(X + 0.2)$ ) these variables in my subsequent analyses. I was able to find CV records for more than 85% of entrepreneurial advisors' students.

## 4. Estimation Strategy and Results

### 4.1. Potential Confounds

Ideally, to analyze the potential impact of advisors' entrepreneurial activity on their PhD students' innovative and career outcomes, I would be able to isolate entrepreneurial engagement from other factors that could explain both entrepreneurial activity and student outcomes. One such confounding factor is selection. For one, professors are likely to select into entrepreneurship based on their unique characteristics. For another, students are likely to choose an advisor based on their unique characteristics and attraction to the topic of research, as are PIs likely to pick a certain type of student to work in their labs. The transition into entrepreneurship

could therefore entail fundamental changes in the composition of PhD students whom professors advise. For example, entrepreneurial professors could deliberately pick students who fit the demands of their startup/commercial interests and may already be relatively less suited for academia before starting their PhDs.<sup>17</sup> In turn, students less interested in an academic career or who are more commercially oriented could pick entrepreneurial professors over other more academically oriented ones.

Another threat is presented by omitted variable bias, meaning that any results I find could be driven by specific features of PIs, students, the research environment, time trends, and the like that the econometrician cannot observe. For example, those professors who transition into entrepreneurship may be different from other professors along certain dimensions such as ability, personal traits (e.g., related to taking initiative and exercising leadership; Feldman et al., 2019), and social skills (that could give them a competitive edge in fundraising or networking). If these traits also induce latent entrepreneurial professors to be different advisors (e.g., in terms of training quality) than those professors who never transition into entrepreneurship, these traits may mask the true impact engagement in entrepreneurial activity has on students. It is also feasible that certain academic life cycle trends, for example, associated with achieving tenure milestones or age, may coincide with a PI's decision to engage in entrepreneurship and that these natural shifts in attention are driving my results (Levin and Stephan 1991). Furthermore, it is possible that, given trends in the PI's field of research, opportunities arise shaping both the likelihood of a PI becoming an entrepreneur and students' scientific productivity and career choices.

Provided the daunting challenges presented in establishing a causal relationship between entrepreneurial activity and PhD student outcomes, my approach is primarily to establish whether there is a relationship between having an entrepreneurial PI with different PhD student outcomes or not and what the directionality of that relationship is on average. This is my baseline. I then address concerns related to omitted variable bias and selection following a step-by-step approach using a host of different controls and estimation techniques to assess the bias that other professor and laboratory-specific features, life cycle trends, or opportunity-related factors are potentially introducing to my main, more "naïve," results. I complement these findings with anecdotal evidence obtained through more than 20 hours of interviews with faculty and students, which I had conducted prior to my archival data analysis. Finally, I assess two potential mechanisms proposed in the literature and rooted in the *raison d'être* of the university that could explain my findings: (1) a PI's influence on a student's

**Table 1.** Summary Statistics: Students of Entrepreneurial PIs

	Minimum	Mean	Median	Maximum
<b>Students</b>				
ePI (continuous)	0.00	2.39	2.00	9.00
ePI (=0/1)	0.00	0.63	1.00	1.00
Duration of PhD	1.00	4.96	5.00	11.00
<b>Gender</b>				
Female	0.00	0.22	0.00	1.00
<b>Departments</b>				
AERO	0.00	0.03	0.00	1.00
BIOMED	0.00	0.09	0.00	1.00
CHEM	0.00	0.04	0.00	1.00
CHEME	0.00	0.13	0.00	1.00
CIVIL	0.00	0.02	0.00	1.00
CS	0.00	0.09	0.00	1.00
ECE	0.00	0.33	0.00	1.00
MATERIALS	0.00	0.11	0.00	1.00
ME	0.00	0.15	0.00	1.00
<b>Ethnicity</b>				
Asian	0.00	0.58	1.00	1.00
Black	0.00	0.03	0.00	1.00
Hispanic	0.00	0.03	0.00	1.00
Two or more	0.00	0.02	0.00	1.00
White	0.00	0.35	0.00	1.00
<b>Other characteristics</b>				
U.S. citizen	0.00	0.38	0.00	1.00
Previous GPA	2.31	3.61	3.65	4.00
Verbal GRE	131.00	155.00	156.00	170.00
Quant. GRE	144.00	162.77	164.00	170.00
Previous Master's degree	0.00	0.21	0.00	1.00
Pre-PhD publication record	0.00	0.31	0.00	1.00
CV record	0.00	0.85	1.00	1.00
Job prior to PhD	0.00	0.19	0.00	1.00
Previous degree from top-tier university	0.00	0.13	0.00	1.00
<b>Outcomes during PhD</b>				
Patents	0.00	0.34	0.00	17.00
Citation-weighted patents	0.00	1.92	0.00	95.00
Publications	0.00	7.00	5.00	61.00
Highly cited publications	0.00	3.30	2.00	51.00
First-authored publications	0.00	3.17	2.00	20.00
Coauthored with advisor	0.00	3.93	2.00	40.00
Citations	0.00	225.12	59.00	5625.00
Av. journal impact	0.00	2.70	1.56	39.14
Peer-reviewed conference proceedings	0.00	3.95	2.00	42.00
<b>Outcomes after PhD</b>				
Patents	0.00	0.83	0.00	21.00
Citation-weighted patents	0.00	2.75	0.00	112.00
Publications	0.00	6.50	3.00	106.00
Highly cited publications	0.00	2.86	1.00	63.00
<b>First job</b>				
Academia/National Laboratory	0.00	0.42	0.00	1.00
Industry	0.00	0.57	0.00	1.00
Founder	0.00	0.01	0.00	1.00
<b>PI characteristics at entry of student</b>				
Female	0.00	0.06	0.00	1.00
Age	25.00	44.59	43.00	73.00
Full professor	0.00	0.55	1.00	1.00
Size of cohort (by year)	1.00	2.46	2.00	8.00
Observations	647			

*Notes.* This table displays summary statistics for the students of entrepreneurial PIs and the PIs themselves. The values displayed reflect the characteristics of the PIs at the time of entry of the student.

research orientation and (2) the PI's engagement in a student's development as an independent researcher.

**4.1.1. Student-Level Outcomes During the PhD Program.** In this section, I present the main student-level results using both aggregate cross-sectional and student panel models.

First, I examine the aggregate cross-sectional results to quantify the correlation of supervision by an entrepreneurial PI with students' outcomes over the duration of the PhD program. In this model, I include respective fixed effects related to specific PIs, years, and fields of research to keep unobservable features of individual advisors, such as ability, and social skills constant, as well as year or field specific changes. Cohorts of PIs' students should be equally affected by these unobservable factors. The equation I estimate on the student level ( $s$ ) is displayed here, where  $f_p$  represents advisor fixed effects,  $f_t$  represents start-year fixed effects,  $f_m$  stands for a student's major,  $X_s$  represents student controls, and  $\epsilon_{s,p,t,m}$  is the error term. Robust standard errors are clustered on the professor and year level to account for intragroup correlation:

$$I_{s,p,m,t} = \alpha ePI_{s,p} + f_p + f_t + f_m + X_s + \epsilon_{s,p,t,m}. \quad (2)$$

In Equation (2),  $ePI_{s,p}$  is the main independent variable of interest, which I measure in different ways: (a) using an indicator equal to one denoting if a student was ever supervised by a PI actively engaged in creating a startup, (b) using the number of years supervised by an entrepreneurial professor, and (c) using the number of years supervised by an entrepreneurial professor divided by the duration of the PhD program. The outcome variable  $I_{s,p,m,t}$  refers to the innovative output of a student  $s$  during the PhD program.<sup>18</sup> These outcomes are the total amount of patents, citation-weighted patents, publications, and highly cited publications a student produces during the PhD program. The *Student Controls* <sub>$s$</sub>  I include are gender, ethnicity, nationality, incoming GRE, and GPA scores, as well as indicators for students' previous degree level, that is, having a master's degree prior to enrolling in the PhD program.

Table 2 displays the results from estimating Equation (2). In Panel A, I report student outcomes using an indicator equal to one if a student was ever exposed to an entrepreneurial advisor during the PhD, and I display the results for *Student controls* <sub>$s$</sub> . The variable *Gender* equals one if the student is male, the variables *Asian*, *Black*, and *White* indicate the ethnicity of the student (Hispanic and other are the omitted category), and *U.S. citizen* indicates whether a student is a U.S. citizen or not. I further control for a student's score on the quantitative section of the GRE test and a student's incoming GPA score. *Master's degree* equals one if the student completed a master's degree prior

to enrolling in the PhD program. In Panel B, I report student outcomes using a continuous measure of years supervised by an entrepreneurial advisor. Panel C displays outcomes using relative supervision (continuous measure of exposure divided by PhD duration). Over all specifications, I find that being supervised by a PI engaged in entrepreneurship is associated with negative publication outcomes, and I do not find a consistent relationship with patenting outcomes. This finding holds when including an interaction term between  $ePI$  and *executive*, which is an indicator equal to one if the advisor holds an executive leadership position in the startup as reported in the online appendix, Table A4. This information was collected through web searches of each startup. Taking the coefficients reported in Table 2, Panel A, the results suggest that supervision by a PI engaged in entrepreneurship is associated with a decrease from the respective mean of about two publications and one highly cited publication during the PhD program. In results left unreported, I fail to detect a relationship between laboratory size and student outcomes by including an interaction term with laboratory size (and different laboratory size cutoffs) and a PI's entrepreneurial engagement.<sup>19</sup>

To address the concern that potential life cycle effects are confounding the results, I include a variable capturing professors' time from tenure in Table 3 (Panel B). Next, I include professor fixed effects times year trends to Equation (2). As reported in Table 3, Panel C, the magnitude of the coefficients for all measures of publication output almost doubles (please refer to Table A5 of the online appendix for the full results). This suggests that the coefficients presented in Table 3 without inclusion of life cycle effects or trends may be considered more conservative results.<sup>20</sup> In terms of patenting output, there does not seem to be a relationship that is statistically significant on conventional levels. For the purpose of this analysis, I assume a linear relationship of professor-year trends, although other functional forms are feasible. In Table 3, Panel D, I further include major  $\times$  year fixed effects to control for new commercialization opportunities that may potentially drive both entrepreneurial engagement and student outcomes. For additional robustness, I control for nonlinearities, which may arise given potential tenure and age effects by including interactions between professor rank<sup>21</sup> and exposure to an entrepreneurial PI and interactions with different age percentiles instead of professor-year trends. These results are reported in Table A7 of the online appendix.<sup>22</sup>

**4.1.2. What Determines Having an Entrepreneurial PI?** The previous set of results I report deal with certain issues pertaining to omitted variable bias on the side of professors and students. Nonetheless, the concern still

**Table 2.** PhD Productivity During the PhD Program (OLS Results)

During PhD (in log)	Patents		Publications	
	Amount (1)	Citation weighted (2)	Amount (3)	Highly cited (4)
Panel A				
<i>ePI</i> (=0/1)	0.123 (0.106)	0.163 (0.168)	−0.264*** (0.0636)	−0.335*** (0.0919)
<i>Gender</i>	0.126*** (0.0280)	0.140** (0.0473)	0.213*** (0.0666)	0.179** (0.0641)
<i>White</i>	0.0500 (0.0726)	0.0504 (0.111)	0.573*** (0.174)	0.400** (0.156)
<i>Asian</i>	0.0995 (0.0872)	0.119 (0.113)	0.688*** (0.140)	0.380** (0.138)
<i>Black</i>	−0.0665 (0.0849)	−0.0882 (0.126)	0.0889 (0.232)	−0.0218 (0.216)
<i>U.S. citizen</i>	0.0502 (0.0532)	0.000751 (0.0672)	0.0120 (0.100)	−0.00364 (0.0616)
<i>Quant. GRE</i>	−0.00101 (0.00229)	−0.00799* (0.00428)	−0.00193 (0.00722)	−0.00650 (0.00724)
<i>Previous GPA</i>	0.104** (0.0479)	0.0735 (0.0827)	0.226** (0.0998)	0.0952 (0.104)
<i>Master's degree</i>	−0.0236 (0.0452)	−0.0293 (0.0547)	0.0587 (0.0841)	0.0474 (0.0719)
<i>R</i> <sup>2</sup>	0.275	0.275	0.411	0.383
Panel B				
<i>ePI</i> (continuous)	−0.0233 (0.0212)	−0.0212 (0.0374)	−0.109*** (0.0238)	−0.121*** (0.0249)
Student controls	Yes	Yes	Yes	Yes
<i>R</i> <sup>2</sup>	0.275	0.274	0.413	0.386
Panel C				
<i>ePI</i> (relative)	−0.0456 (0.113)	−0.0674 (0.196)	−0.334** (0.112)	−0.400*** (0.125)
Student controls	Yes	Yes	Yes	Yes
<i>R</i> <sup>2</sup>	0.274	0.274	0.411	0.383
Major fixed effects	Yes	Yes	Yes	Yes
Professor fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,536	2,536	2,536	2,536
Number of professors	434	434	434	434

*Notes.* This table displays the results from estimating Equation (2). In Panel A, I report student outcomes using an indicator equal to one if a student ever worked for an entrepreneurial PI during the PhD. The variable *Gender* equals to one if the student is male. *White*, *Asian*, and *Black* indicate a student's self-reported ethnicity (the group of students of Hispanic origin and those who report two or more ethnicities is the omitted category), and *U.S. Citizen* indicates whether a student is a U.S. citizen or not. I further control for a student's score on the quantitative section of the GRE test and a student's incoming GPA score. *Master's degree* equals one if the student completed a master's degree prior to enrolling in the PhD. These controls are denoted as *Student controls* in Panels B and C. In Panel B, I report student outcomes using a continuous measure of years working with an entrepreneurial PI. Panel C displays outcomes using a relative measure (time the student's PI was engaged in entrepreneurship divided by PhD duration). Standard errors are reported in parentheses and are clustered on the professor and year level.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

remains that the type of students joining a PI's laboratory could be changing as a function of professors' entrepreneurial activity. To address this type of sorting, I first collect information from the PhD program coordinators in mechanical engineering and chemical and biomolecular engineering on how their schools organize the matching process. In the timespan I examine (there have been changes in more recent years), students centrally apply to the program and not to a specific advisor. PhD applicants are then accepted to the school based on a committee's assessment of an applicant's

grades, test scores (GRE, GPAs, and TOEFL for foreign students), and overall application package. Once admitted to the program, PhD students meet with all available PIs (in some departments only for 30 minutes) to identify the research projects and professors that they are most interested in working on and with. Typically, before the end of the first semester, PhD students and professors have established a match.

In what follows, I will provide qualitative evidence for this process from mechanical engineering. When asked why they decided to join the university, a student

**Table 3.** Comparison of Coefficients

	Patents		Publications	
	Amount (1)	Citation weighted (2)	Amount (3)	Highly cited (4)
During PhD (in log)				
Panel A: Professor fixed effects and year fixed effects model <sup>a</sup> ( $n = 2,536$ )				
ePI (= 0/1)	0.123 (0.106)	0.163 (0.168)	−0.264*** (0.0636)	−0.335*** (0.0919)
Panel B: Professor fixed effects, year fixed effects, time from tenure fixed effects ( $n = 2,468$ )				
ePI (= 0/1)	0.144 (0.100)	0.199 (0.163)	−0.245*** (0.0722)	−0.336*** (0.0957)
Panel C: Professor fixed effects × year model ( $n = 2,536$ )				
ePI (= 0/1)	−0.0232 (0.185)	−0.0309 (0.282)	−0.597** (0.235)	−0.585** (0.224)
Panel D: Professor fixed effects × year model and year fixed effects × major fixed effects ( $n = 2,499$ )				
ePI (= 0/1)	0.0267 (0.168)	0.00478 (0.254)	−0.667** (0.232)	−0.661*** (0.217)
Panel E: Double LASSO model ( $n = 2,649$ )				
ePI (= 0/1)	0.0923 (0.100)	0.140 (0.148)	−0.296** (0.142)	−0.321** (0.153)
Panel F: CEM model ( $n = 157$ )				
ePI (= 0/1)	−0.165 (0.110)	0.0400 (0.197)	−0.488** (0.146)	−0.473** (0.154)
Panel G: IPW model (ATE statistic reported) ( $n = 562$ )				
ePI (= 0/1)	0.0986 (0.0973)	0.130 (0.119)	−0.486*** (0.0912)	−0.516*** (0.136)
POmean	−1.194*** (0.0687)	−1.151*** (0.105)	1.685*** (0.103)	0.758*** (0.129)
Panel H: Panel with student fixed effects <sup>b</sup> ( $n = 16,964$ )				
ePI-Post × $\tau_{s,t}$	0.00295 (0.00691)	−0.00327 (0.0169)	−0.0708*** (0.0164)	−0.0348*** (0.0117)

*Notes.* This table presents a summary of the coefficients on student outcomes obtained using different estimation techniques. The number of observations differs given constraints of the models, for example, dropping singleton observations. CEM, coarsened exact matching model; IPW, inverse probability of treatment model (overlap assumptions are not violated), which is estimated as follows, where the denominator of  $\omega_s$  is the conditional probability that a student was assigned their PI  $p$ :

$$\omega_s = \frac{1}{\text{PROB}(T_s = p | X_s^p)}.$$

Assuming that all relevant factors determining matches are observed and included in  $X$ , weighting by  $\omega_s$  effectively creates a pseudo-population of students in which  $X$  no longer predicts assignment.

<sup>a</sup>Those that are taken from other tables in the main paper.

<sup>b</sup>Panel H provides results from estimating student outcomes at the student-year level. The coefficient of interest is  $ePI\text{-}Post \times \tau_{s,t}$ . The variable  $ePI\text{-}Post$  equals one if the student had an entrepreneurial advisor in a given year of the PhD program and  $\tau_{s,t}$  measures a student's time in the program (student and professor fixed effects, as well as time year trends are included). Robust standard errors are reported in parentheses. For Panel H these are on the student level, and in a given year.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\*  $p < 0.01$ .

mentioned the following: “The reason I decided to come to [UNIVERSITY], was because of fit. I am pretty sure [UNIVERSITY] has the largest [field of major] department in the country.” The student applied to a low double-digit number of schools close their hometown, close to their undergraduate degree granting institution and general top programs. The university I examine falls in the latter category. I further asked why they picked their advisor. A PhD student stated that their advisor (an entrepreneur) “is really innovative, has done a lot of work with [main topic of interest], and is pushing the

boundary of the field.” Another student from a different laboratory said, “I started working with [advisor] because [advisor] had funding available and also because I am generally interested in [topic].” The professor had told them: “If you are going to join the group, this is the project I have; I have funding for.” These interviews also unveiled that PhD projects are often “continuations of students’ work who have left or spawned additional questions” determined by the PI. Regarding the other students in the laboratory, one PhD candidate mentioned: “We’re all pretty similar.

[Advisor] picks similar people.” All in all, this suggests that students are attracted to the university because of its high research reputation, and students prefer advisors with a strong publishing record but are constrained by funding in terms of the final PI match and project selection.

Based on this information, which I use as guidance, I further implement a machine learning algorithm that makes use of the many observables I have at my disposition. As suggested by Belloni et al. (2014a, b), the double-LASSO approach can be used for inference even when certain relevant variables are excluded. The approach is called double because it consists of two steps that both use a LASSO selection procedure. The first step involves the selection of covariates that predict the likelihood of working with an entrepreneurial advisor, whereas the second step requires the identification of the covariates that predict student productivity (Belloni et al. 2014a). The union of the control variables selected from each step ultimately defines the set of variables used in the outcome regression equations. I repeat the second step of the double LASSO procedure for each outcome. In my setting, I include information on gender, ethnicity, nationality, GRE scores, GPAs, previous degrees, quality of the previous degree-granting institution, job experience, pre-PhD publication, professors’ publication and patenting record prior to a student’s entry, laboratory size, federal funding information, year, professor, and major fixed effects, as well as respective interactions. Of these 1,275 high-dimensional controls, an average of 20 variables were selected by the machine learning program. The first step reveals the importance of professors’ federal funding (0.003;  $p = 0.001$ ) and publication record (0.082;  $p = 0.000$ ), which I measure as the amount in the five years prior to the focal student’s entry, as well as the year (0.006;  $p = 0.003$ ) in determining a match with an entrepreneurial PI. Revisiting the interview evidence presented previously, this appears to be consistent. The second step results are reported in Table 3, Panel E, and are also consistent with my prior findings.

Next, I empirically assess whether incoming characteristics of students predict that the PIs they join were ever entrepreneurs during their PhD program or started a company in the five years prior to a student’s entry. For the purpose of my research question and analysis, this is the relevant matching dimension given my concern about sorting as a function of an advisor’s entrepreneurial behavior. The characteristics of students I examine are a student’s gender (equal to one if female), a student’s ethnicity (Hispanic and other is the omitted category), the quality of a student’s previous degree-granting institution, a student’s incoming GPA and GRE scores (log), nationality (equal to one if the student is a U.S. citizen), previous work experience (*Prev. Job Experience*), and student’s previous publication

record (*Pre-PhD publication record*; equal to one if the student had any). I choose these characteristics based on results reported in the online appendix, Table A8, where I regress student outcomes on observable characteristics and on prior literature suggesting links between individuals’ entrepreneurial ability and prior work experience (Lazear 2005). As displayed in Table 4, columns 1 and 2, the magnitudes of the coefficients are small, and only the variable *Pre-PhD publication record*, a possible proxy for students’ academic ability, is statistically significant on conventional levels. The relationship between *Pre-PhD publication record* and working for a PI who is already an entrepreneur is positive, which suggests that students of higher academic quality may be selecting into labs run by entrepreneurial PIs. Naturally, this approach cannot capture differences in unobservable characteristics such as personality. To bias my results upward, however, students with personality characteristics that correlate negatively with academic excellence (but positively with a pre-PhD publication record) would have to select into entrepreneurial labs. This is unlikely to align with the correlations I find on the observable characteristics in Table 4.<sup>23</sup>

To unveil potential differences related to pre-entry knowledge about PIs, I further distinguish between those students coming from other institutions for their PhD and those who graduated from the home institution. Students who received their undergraduate degrees at the home institution should be the best informed about the PIs they could potentially work with. As displayed in columns 3 and 4 of Table 4, it appears that a student’s incoming GPA predicts matching with an entrepreneurial advisor only if the advisor becomes entrepreneurial while the student is already part of the laboratory. Because a student’s GPA predicts the number of papers a student produced during the PhD (see the online appendix, Table A8), this could explain some of the negative effect, if the higher scoring students of the best-informed population are now no longer joining labs of entrepreneurial advisors. However, because this only applies to a restricted population, this is unlikely driving my full results. Including an interaction with undergraduate degree attained at home institution, my baseline results remain similar as do those interacting *ePI* with an indicator equal to one if the student had an incoming GPA score of 3.83 or higher (75th percentile). Extremely high-achieving students seem to be able to somewhat compensate for the negative relationship between having an entrepreneurial PI and their amount of publications. These results are reported in the online appendix, Table A10.<sup>24</sup>

Although I find only weak evidence of sorting into labs headed by entrepreneurial PIs, the concern still remains that my main results may be driven by changes in the composition of students as a function of

**Table 4.** What Predicts Having an Entrepreneurial PI?

	Professor was a founder			
	All		Undergraduate at home institution only	
	During PhD (1)	Pre-entry (5 years) (2)	During PhD (3)	Pre-entry (5 years) (4)
<i>Gender</i>	−0.0127 (0.0181)	−0.00895 (0.00635)	−0.0538 (0.0609)	−0.0667 (0.0584)
<i>White</i>	−0.0545 (0.0541)	0.00131 (0.0191)	−0.0893 (0.122)	−0.0468 (0.0891)
<i>Asian</i>	−0.0556 (0.0535)	0.0120 (0.0264)	−0.0509 (0.108)	−0.0621 (0.0465)
<i>Black</i>	−0.0888 (0.0533)	−0.0189 (0.0146)	−0.179 (0.152)	−0.130 (0.0917)
<i>U.S. citizen</i>	−0.0151 (0.0246)	0.00253 (0.0133)	−0.0294 (0.0816)	−0.0434 (0.0746)
<i>Verbal GRE</i>	0.000497 (0.000820)	−0.000355 (0.000723)	0.00124 (0.00254)	−0.00167 (0.00193)
<i>Quant. GRE</i>	0.00301 (0.00191)	−0.000217 (0.00172)	0.00222 (0.00456)	0.0000498 (0.00168)
<i>Prev. GPA</i>	0.00300 (0.0271)	0.0110 (0.0163)	0.194*** (0.0467)	0.0754 (0.0562)
<i>Master's degree</i>	−0.0249 (0.0200)	−0.0119 (0.00997)	−0.00553 (0.0467)	0.0296 (0.0223)
<i>Degree from top-tier university</i>	0.0292 (0.0560)	0.0315 (0.0284)		
<i>Prev. job experience</i>	0.0114 (0.0163)	−0.00366 (0.0103)	0.0209 (0.0394)	0.0321 (0.0257)
<i>Pre-PhD publication record</i>	0.00356 (0.0145)	0.0153* (0.00766)	−0.0241 (0.0275)	−0.0274 (0.0306)
Department fixed effects	Yes	Yes	Yes	Yes
Major fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,648	2,648	329	329
R <sup>2</sup>	0.0904	0.0503	0.189	0.167

*Notes.* This table displays the OLS results from estimating the likelihood that a student has a PI who was a founder during the student's PhD program (*During PhD*) and a PI who was a founder in the five years prior to the student's entry (*Pre-Entry (5 years)*). The variable *Gender* equals to one if the student is male, *Ethnicity* is equal one if the student is white, and *U.S. citizen* indicates whether a student is a U.S. citizen or not. I further control for a student's score on the different sections of the GRE test and a student's incoming GPA score (*Previous GPA*). *Master's degree* equals one if the student completed a master's degree prior to enrolling in the PhD, and *Degree from top-tier university* equals one if the student's prior degree was attained at a top-tier university. *Prev. job experience* equals one if a student had a job prior to starting the PhD, and *Publications pre-PhD* equals one if the students ever published prior to joining the PhD program. Columns 1 and 2 are for all students, and columns 3 and 4 are restricted to those students who received their undergraduate degree at the PhD granting institution. I include department, major, and year fixed effects. Standard errors are reported in parentheses and are clustered on the major and year level.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

entrepreneurial engagement. For further robustness, I apply a CEM model. The results are reported in Table 3, Panel F, and are similar to my main results. In the context of this paper, the CEM algorithm ensures that students who are exposed to an entrepreneurial PI (the treated sample) are compared with a valid group of counterfactual students (the control sample) by balancing these two groups based on predetermined, observable variables (Iacus et al. 2012). Because one of the main concerns is that students may select different types of advisors and that this is correlated with outcomes, I identify pre-entry professor characteristics, which I use to create a large number of strata to cover the joint distribution of observable characteristics I use

to implement this approach. I then allocate students to corresponding strata and retain all strata that have at least one treatment and one control observation. Each match is assigned a weight. The characteristics I use are as follows: professors' age (in octiles), an indicator whether a professor applied for a patent in the five years prior, the number of publications a professor had in the five years prior to a student's entry (in quintiles), and a professor's average student publication in the five years prior (in terciles), an indicator equal to one if the professor was a full professor, department, and year. Table A11 (online appendix) presents mean differences of the matched sample of treated students with the corresponding controls. Matching

considerably reduces the differences, although it also substantially decreases the sample size, which is why I use the CEM approach as robustness only. However, and importantly, none of the differences remain statistically significant at conventional levels.

I further estimate an inverse probability weighting approach (IPW) following Azoulay et al. (2017). The IPW estimator is a useful tool when a controlled experiment is not feasible, but fine-grained data are available to model selection (Azoulay et al. 2017). The outcome measure is weighted by the inverse of the probability that an individual with a given set of covariates is assigned to their treatment (propensity score). In short, the goal is to estimate the potential outcome that would be observed if a student were assigned treatment to an entrepreneurial PI and then compare the mean outcome if all students in the population were assigned treatment (Angrist and Pischke 2008). To pick a suitable set of controls, I use those suggested by Azoulay et al. (2017): same gender, same quality of previous degree granting institute, same ethnicity, same nationality, and department, major and year fixed effects. I restrict the analysis to those students of professors who ever were founders.

I present the results from estimating the IPW model in Table 3, Panel G. Columns 1 and 2 show the results for patenting outcomes, and column 3 and 4 show results for publication output. All outcomes are in log. Overall, the results confirm earlier findings. The estimates in column 3, for example, suggest that exposure to an entrepreneurial PI may decrease students' log publications by an average of 0.486 from the average of 1.69 for students' who are not exposed. Postestimation tests indicate that the overlap assumption is not violated.<sup>25</sup>

Finally, I display results where I exploit within-student variation of outcomes over time to assess how supervision by an entrepreneurial PI impacts a student's productivity during the PhD on the year level. In this difference-in-differences type model, I apply student fixed effects allowing me to hold time-invariant student characteristics, including talent, social intelligence, and personality, constant. Using this approach, I estimate the number of patents, citation-weighted patents, publications, and highly cited publications produced in a given year from entry to the PhD until 5 years after as follows:

$$I_{s,t} = \alpha ePIPost_{s,t} \tau_{s,t} + \beta ePIPost_{s,t} + \tau_{s,t} + f_s + f_{p*} + \epsilon_{s,t,p} \quad (3)$$

where  $I_{s,t}$  denotes a student's output. The variable  $ePIPost_{s,t}$  equals one in the period after the student's PI starts a company. The vector  $\tau_{s,t}$  encompasses indicators for a student's experience for each year from the moment the student enrolls in the PhD program

until a year after graduation. Finally,  $f_s$  denotes student fixed effects, and  $f_{p*}$  is the professor fixed effects times year trends. I cluster standard errors on the student level. The results are reported in Table 3, Panel H, where the coefficient of interest,  $\alpha$ , suggests a negative relationship between being exposed to an entrepreneurial advisor and yearly student publication outcomes once the advisor becomes an entrepreneur ( $ePIPost_{s,t} \tau_{s,t}$ ). The patenting outcomes are inconclusive and not statistically significant on conventional levels. All results are similar when using a dummy equal to one as an outcome if a student had at least one patent, citation-weighted patent, publication, and/or highly cited publication. For more detail on these results, please see Table A13 of the online appendix.

#### 4.1.3. Student-Level Outcomes After Graduation.

**4.1.3.1. Productivity After Graduation.** Starting conditions at entry into the labor force have been found to have long-term consequences for individuals' careers and scientific output (Oyer 2006, Oreopoulos et al. 2012). In this section, I examine whether and to what extent being supervised by an entrepreneurial PI has similar persistent effects on students' postgraduation productivity and their subsequent careers. I estimate Equation (2) using the number of patents, citation-weighted patents, publications, and highly cited publications that a student has one to five years from graduation as the outcomes variables.

Table 5, Panel A, displays the results for postgraduation outcomes. As shown in columns 3 and 4, being supervised by a PI who is actively engaged in entrepreneurship during the PhD is associated with a negative impact on the overall amount and quality of publication output after graduation. Conversely, as reported in columns 1 and 2, there does not seem to be a persistent relationship with patenting output.<sup>26</sup> In Panel B, I estimate the same models and include indicators for the type of first job (academia and laboratory, industry is the omitted category) because this may have consequences for the type of output produced (the drop in observations is due to missing job information). Across all specifications, the relationship with  $ePI$  persists for both publication outcomes.

**4.1.3.2. Career Outcomes.** Next, I examine whether and to what extent being exposed to an advisor engaged in entrepreneurship is correlated with PhD students' career outcomes. The two career paths I study in more detail are the academic and private sector trajectory.<sup>27</sup> To provide insight on the relationship of engagement in entrepreneurship with these career trajectories, I first estimate a linear probability model applying student controls, professor, major, and start-year fixed effects, and I relate these to the likelihood

**Table 5.** Post-PhD Productivity (OLS Results)

One to five years after PhD (in log)	Patents		Publications	
	Amount (1)	Citation weighted (2)	Amount (3)	Highly cited (4)
Panel A: Without first employment				
ePI (= 0/1)	−0.0727 (0.0720)	−0.0166 (0.112)	−0.195* (0.111)	−0.183* (0.0974)
Observations	2,303	2,303	2,303	2,303
R <sup>2</sup>	0.274	0.276	0.293	0.304
Panel B: With first employment				
ePI (= 0/1)	−0.142 (0.0881)	−0.179 (0.117)	−0.262** (0.108)	−0.274*** (0.0913)
First job	Yes	Yes	Yes	Yes
Observations	1,638	1,638	1,638	1,638
R <sup>2</sup>	0.323	0.323	0.366	0.368
Student controls	Yes	Yes	Yes	Yes
Major fixed effects	Yes	Yes	Yes	Yes
Professor fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

*Notes.* This table displays the results from estimating Equation (2) predicting student patenting and publishing output within one to five years after completing their PhDs. In Panel B, I include an indicator for the student's first employment type on graduation (academia and laboratory, industry is the omitted category). Student controls are those described in Table 2. Differences in observations are due to missing information from CVs. Standard errors are reported in parentheses and are clustered on the professor and year level.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

of finding a first position in academia, as a professor, and, conditional on going the private sector route, the likelihood of working for a small (<10 employees), a large (>1,000 employees), an old (founded at least 65 years before student exit), a young (founded at most 5 years before student exit), a consulting, and a prestigious firm (as listed in LinkedIn's Top 50 Companies in 2018: [linkedin.com/pulse/linkedin-top-companies-2018-where-us-wants-work-now-daniel-roth/](https://www.linkedin.com/pulse/linkedin-top-companies-2018-where-us-wants-work-now-daniel-roth/)). The private sector categories are not mutually exclusive, and I adopt a broad definition of academia by also including positions in national research institutions such as the Oak Ridge National Laboratory or the Sandia National Laboratories. As displayed in Table 6, column 1, the results do not suggest a change in the likelihood to pursue a job in academia on graduation. This finding is consistent with the evidence (Stephan 2012, Sauermann and Roach 2016) that remaining in academia on graduation, usually in a temporary postdoc position, has become common and should not be too sensitive to training received. The results in column 2 point to a decrease in the likelihood of assuming a faculty position, which is accompanied with an increase in the likelihood of finding a first position at a consulting firm for those students who pursue the private sector route (column 7). Further results left unreported do not reveal any differences in terms of having/negotiating a job offer at graduation or still being on the quest for a position.

To ensure that the results are not driven by selection bias induced through missing CV information, I

examine the relationship between supervision by an entrepreneurial PI and other student characteristics with the retrieval of a student's CV by the research team. As shown in column 9 of Table 6, having an entrepreneurial PI does not seem to be associated with CV retrieval. Ethnicity is related with the likelihood of having a CV as is a student's incoming GPA and U.S. citizenship status.

## 5. Potential Mechanisms

As presented in my previous set of results, my findings suggest that a PI's engagement in entrepreneurship is negatively associated with their students' scientific productivity during the PhD and that this seems to have a persistent relationship with post-PhD scientific productivity and on job outcomes. It remains an open question, however, through which channels this negative relationship on traditional academic output operates. In what follows, I explore two possible mechanisms: Subtle changes in PIs' attention and research orientation may lead to (1) shifts in students' research orientation and/or (2) shifts in engagement in student development (Kenney 1987). A summary of the predictions and measurement can be found in Table A14 of the online appendix.

### 5.1. Influence on Research Orientation

**5.1.1. Direction of Research.** As their advisors become engaged in entrepreneurship, students may adopt more commercially oriented research attitudes from them. This may entail (a) a relative shift to patenting

**Table 6.** Student Career Outcomes: Linear Probability Models

	Academia		First industry job at firm that is						CV record (9)
	First (1)	Professor (2)	Young (3)	Small (4)	Old (5)	Large (6)	Consulting (7)	Prestigious (8)	
ePI (= 0/1)	0.0815 (0.0495)	−0.0607** (0.0243)	−0.141 (0.105)	−0.182* (0.0961)	0.0672 (0.107)	0.125 (0.0863)	0.0610** (0.0251)	−0.0265 (0.0636)	−0.0238 (0.0301)
Student controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Professor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	0.42	0.18	0.47	0.30	0.19	0.33	0.04	0.11	0.82
Observations	1,860	1,860	976	976	976	976	976	976	2,536
R <sup>2</sup>	0.307	0.331	0.308	0.341	0.389	0.361	0.352	0.393	0.214

*Notes.* This table displays the results from estimating students' career outcomes. Columns 1 and 2 examine those outcomes related to academia, columns 3–8 display the results pertaining to industry, and column 9 reports the likelihood of retrieving a CV record as a function of having an entrepreneurial advisor and the student controls described in Table 2. Firms are defined as young if the founding date of the firm was five or less years prior to a student's graduation year, and they are defined as old if the founding date of the firm was 65 or more years prior to a student's graduation year. Small firms have less than 10 employees, and large firms have 1,000 or more employees as of 2021. Standard errors are clustered at the professor and year level.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

activity and (b) a focus on research related to the advisor's entrepreneurial venture. These potential drivers should be detectable by examining students' research output in more detail, for example, by shining light on the relative amount of commercial output to scientific output a student produces and by assessing potential changes in students' dissertation research.

My findings, as displayed in Table 7, Panel A, column 1, suggest that students' patenting amount relative to publication does not change significantly, although there may be a slight shift toward more commercially oriented output given the positive sign on

the coefficient. The relationship, however, remains statistically insignificant on conventional levels. As suggested by Azoulay et al. (2007), the number of papers a student publishes predicts the number of patents produced.

To assess whether there is potential overlap in a students' dissertation research and their advisor's ventures, I retrieve all dissertations completed by entrepreneurial Pls' students from the university's dissertation repository and compare these 647 dissertations to descriptions of the startups provided to me by the university's venture outreach organization. I read through each of the

**Table 7.** PhD Productivity—Changes in Research Orientation, and Authorship (OLS Results)

	Research orientation				Student development	
	Patents		Publications		First-auth. (5)	W / Advisor (6)
	Amount (1)	Weight. (2)	No. citations (3)	Av. journal impact (4)		
<i>During PhD (in log)</i>						
ePI (=0/1)	0.139 (0.190)	0.187 (0.167)	−0.391*** (0.126)	−0.235** (0.0930)	−0.286** (0.128)	−0.338** (0.135)
ln(Publications)	0.061** (0.0250)	0.0905*** (0.0261)				
R-squared	0.284	0.284	0.410	0.435	0.478	0.513
Mean (not log)	0.22	1.90	155.24	2.38	2.55	2.90
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes
Prof FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2536	2536	2536	2536	2536	2536

*Notes:* This table displays the results from estimating Equation (2), using more nuanced outcomes. These are the amount of patents controlling for publications (including proceedings) a student produced during the PhD (column 1), citation-weighted amount of patents controlling for publications (including proceedings) a student produced during the PhD (column 2), the number of citations (column 3), the average journal impact factor (column 4, higher values represent higher impact), the number of first-authored publications (column 5), and the number of publications co-authored with the student's advisor (column 6). *Student Controls* are those described in Table 2. Standard errors are reported in parentheses and are clustered on the professor and year level.

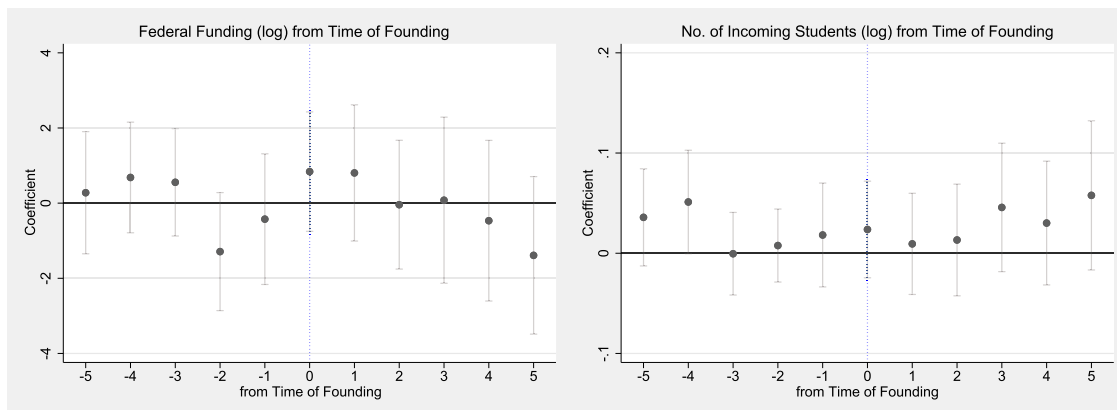
\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

dissertation abstracts and sought help from experts if terms were beyond my expertise. Roughly 55% of the retrieved dissertations have some overlap with the startup, and using the same estimation as described in Equation (2), I find a positive relationship ( $=0.119$ ), albeit not statistically significant on conventional levels ( $p$ -value = 0.158) with being supervised by an entrepreneurial advisor. The effect is primarily driven by those students who graduate in the year the startup is created ( $=0.195$ ,  $p$ -value = 0.083). Only seven dissertations seem to be directly linked to the startup. Overall, the overlap appears to suggest that most of these startups may have been generated out of the PIs' general research program, which goes in line with previous studies examining how scientific opportunities may drive commercial engagement (Azoulay et al. 2007) rather than commercial interest research focus.

Following prior literature, a further possible explanation for the negative relationship between professors' engagement in entrepreneurship and their PhD students' publication output could be related to funding (Perkmann et al. 2013). As a result of engagement in entrepreneurship, or even preceding the transition, it could be that professors experience changes in where they source funding from. As suggested by Lee (2000), this is feasible because academics collaborate with industry, amongst others, to secure funding for their students, equipment, and materials. Generally, the assumption is that this type of involvement will benefit faculty by providing more practical application of their research, but this could also indicate a shift in the type of research faculty undertake or, critical for this context, assign to their students. One way to test this is by examining changes in funding structure

as a function of time from starting a company. Given data disclosure issues, I was only able to obtain information on professors' NSF and National Institutes of Health (NIH) funding. Taking this information and using the approach described in Equation (1) (excluding the cumulative number of coauthors), I detect a slight decrease in federal funding two years prior to startup, although the coefficient is not statistically significant on conventional levels (Figure 6, left). This may indicate two things. One is that the year professors shift their attention to other sources of funding and become more involved in commercialization is earlier than I have measured. Given that two years prior to establishment professors' patenting activity also picks up, this is feasible. The other is that professors tried to receive federal funding but failed to do so, and this is what pushed them toward becoming entrepreneurial. Because funding is also strongly linked to the ability to hire students, I should pick up changes in the ability to attract funding by the number of incoming students in a given year. As displayed in Figure 6 (right), this number does not change. These results are obtained using the same approach described in Equation (1) but not including the cumulative number of coauthors and instead controlling for the number of students already in the laboratory. In results left unreported and available upon request, I also fail to find a relationship of being supervised by an entrepreneurial PI and the type of funding support a student receives (through teaching assistance, research assistance, grants, fellowships, or own funds). Taken together with all the other findings thus far, the explanation that advisors may shift their attention in the two years prior to startup seems more feasible than

**Figure 6.** (Color online) Professor Federal Funding and Number of Students as a Function of Founding a Company



**Notes.** This figure displays the relationship between founding (x axis indicates the time from startup year) and professors' amount of federal funding (left) and number of incoming students (right) (y axis; all outcomes in log). The results are obtained controlling for whether the focal professor has at least one student and using professor and department-year fixed effects. In the figure that displays the number of incoming students, I further control for the number of current students in an advisor's laboratory. Category 5 denotes all years five or more after founding date. The omitted category is six or more years before startup. The dashed vertical line indicates time of founding, and the confidence intervals displayed are at the 95% level. Robust standard errors are clustered on the department-year level.

the lack of laboratory funding from more academic oriented sources to support research.

**5.1.2. Research Scientific Value.** As their advisors become engaged in entrepreneurship, students may adopt less academically oriented research attitudes entailing a drop in the amount of research they produce that is highly valued by the scientific community. In terms of research value, I examine two outcomes that could serve as suitable proxies. These are the number of citations (log) a student receives on the work produced during the PhD, and average journal impact factor, which I measure using the Scimago Journal Ranking ([www.scimagojr.com/journalrank.php](http://www.scimagojr.com/journalrank.php)). As displayed in Table 7, columns 2 and 3, using the approach described in Equation (2) and including the same controls, I find a decrease in students' overall citations and the average journal impact factor of their publications. This suggests that students may be experiencing a decrease in the impact of their research for the scientific research community as their advisors become engaged in entrepreneurship.

**5.1.3. Research Type.** It is possible that once a PI becomes an entrepreneur, the type of research conducted in a laboratory shifts. One form could be toward a stronger practitioner focus. To shine light on this, I create an outcome variable that only counts the number of peer reviewed conference proceedings a student produced during the PhD. In most cases, this type of output channel is faster (pieces are shorter) and relatively more practitioner oriented. Another way to capture changes in the type of research

students produce is using the long-established CHI classification (Narin et al. 1976) to identify the “basic” or “applied” nature of a publication. The CHI journal classification system assigns each bio-medical journal to one of four mutually exclusive research levels, according to their degree of appliedness: I, applied technology; II, engineering-technological mix; III, applied research; IV, basic scientific research. As presented in Table 8, columns 2 to 5, the only category experiencing a relative decrease is the most applied category.<sup>28</sup> Because the classification is only available for bio-medical journals and thus many of the journals students publish in cannot be matched (low mean), I further present the relationship between having at least one publication classified by CHI and an entrepreneurial PI. There does not seem to be a statistically significant relationship (column 6).

## 5.2. Engagement in Student Development

**5.2.1. Apprenticeship-Like Training.** Typically, students are trained by their advisors in an apprenticeship-like manner. As PIs become engaged in entrepreneurship, their focus may shift away from training the students they supervise toward their new role as a founder. One way to assess these possible changes is leaning on authorship conventions in the sciences and engineering, which follow a set of norms and implicit rules. For example, first authorship tends to be assigned to the author who contributed most to a research project, and last authorship is granted to the PI of the main contributing laboratory (Sauermann and Haeussler 2017). Using the same approach as described in Equation (2), I test whether supervision by an entrepreneurial PI is also associated

**Table 8.** PhD Productivity—Type of Output (OLS Results)

	No. conference proceedings (1)	Publications by research level (CHI)				At least one classified (6)
		I (2)	II (3)	III (4)	IV (5)	
<i>During PhD (in log)</i>						
ePI (=0/1)	-0.0175 (0.120)	-0.129** (0.0479)	0.0410 (0.0721)	0.00488 (0.0817)	-0.0472 (0.0560)	0.0393 (0.0314)
ln(Number of Articles)	0.391*** (0.0287)	0.156*** (0.0185)	0.300*** (0.0256)	0.311*** (0.0232)	0.247*** (0.0194)	0.267*** (0.00685)
R-squared	0.620	0.495	0.566	0.592	0.596	0.698
Mean (not log)	2.89	0.08	0.20	0.24	0.18	0.25
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes
Prof FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2536	2536	2536	2536	2536	2536

*Notes:* This table displays the results from estimating Equation (2), using more nuanced outcomes to examine potential relative changes to the type of research students conduct. Controlling for the number of research articles (excluding proceedings) a student produced during the PhD, the outcome variables are as follows. In column 1, the outcome is the number of peer reviewed conference proceedings, in columns 2–5, I use the CHI Research Level classification introduced by Narin, et al. (1976) and differentiate between different research levels: I—Applied technology; II—Engineering-technological mix; III—Applied research; IV—Basic scientific research. Column 6 presents the correlation for the model used with having at least one publication classified by CHI. All other outcomes are in log. *Student Controls* are those described in Table 2. Standard errors are reported in parentheses and are clustered on the professor and year level.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

with drops in first-authored papers and in the number of papers coauthored by a student and their respective PI. In this case, both outcomes serve as proxies for the training a student receives during the PhD program. First-authored publications should capture the extent to which a student has been trained to become an independent researcher, and coauthorship with the advisor should serve as a measure for the amount of publication-specific training a student received from their respective PI. As displayed in Table 7, columns 5 and 6, having an entrepreneurial advisor is associated with a 29% and 34% decrease in the amount of first-authored and advisor coauthored publications, respectively, a student produces during the PhD, suggesting that changes in training intensity are a feasible explanation.

At this point, I revisit my main specification and further investigate whether there is heterogeneity in the relationship as a function of field related idiosyncrasies of how labs are managed. I distinguish between engineering and more basic life sciences given that students in the life sciences tend to be more autonomous and rely less on the overall management of their corresponding labs for the production of output throughout the PhD process (Stephan 2012). Also, the motives to engage in commercial activity differ between engineers and life scientists (Cohen et al. 2020). If managerial changes related to training and mentorship are indeed plausibly driving my results, I would expect an advisor's impact on students' productivity to be weaker. My findings support this explanation. As displayed in Table 9, Panel A, my baseline results are primarily driven by students enrolled in engineering majors, although patenting outcomes appear to be negative for students in the life sciences.

Similarly, I examine potential differences related to students' entry level. A crude distinction can be made based on the aggregate GRE scores students achieved prior to starting the PhD program. Students with higher scores may be better equipped to compensate for reduced training.<sup>29</sup> These students should be less impacted if one driver of the negative relationship is indeed related to changes in student development. As displayed in Table 9, Panel B, my results indicate that in terms of publications, students with higher aggregate GRE scores (>324; 75th percentile) can compensate to some extent. In terms of patenting, the interaction is positive, although statistically insignificant on conventional levels. This may suggest that a certain subpopulation can leverage their advisors' engagement in entrepreneurship better than others. This may also provide some explanation for the inconclusive results on patenting in the main specifications.

Next, I examine differences in the main specification depending on the citizenship of students. Partially given visa restrictions after graduation (OPT is only a limited time option, so recent graduates typically need

to find an organization to host their H1B), international students, for one, are likely to have fewer outside options than U.S. students if they want to stay in the United States. For another, non-U.S. students face larger hurdles to pursue the PhD in the United States in the first place (leaving their home country, extra test requirements, administrative issues, etc.) raising the threshold to complete a PhD in the United States, so those that take the leap may on average have higher "unobservable" academic-oriented ability (and motivation). In addition, the value of a United States-granted patent may be relatively lower for non-U.S. students, because patent protection may not be granted in their home country. Together, this suggests that non-U.S. students may be less flexible to pivot their research orientation, in general, from academic to commercial and suggests that non-U.S. students may have higher motivation to excel at publishing regardless of the training they receive. When including an interaction between *ePI* and *U.S. citizen*, I find that the main results hold but are weaker. U.S. students that are advised by an entrepreneurial advisor seem to fair the worst in terms of publication output. Generally, having a U.S. citizenship is associated with more patents, although there does not seem to be a differential relationship when advised by an entrepreneurial advisor. This provides additional support for the student development explanation and indication of possible constraints in shifting research orientation among certain students.<sup>30</sup>

Finally, I assess if there are any potential differences by the quality of a startup, which I proxy using the amount of earliest stage (preseed) funding a startup raised. These results are displayed in Table 9, Panel D, and unveil that students advised by a PI who raised above the median in earliest stage funding experience a boost in the number of patents they produce. Regarding the other outcomes, there are no significant differences on conventional levels.

**5.2.2. Mentorship.** A further potential driver of my baseline results could be that the entrepreneurial engagement of a professor leads to a reduction in the execution of one of the most critical roles advisors' assume: mentoring. Mentoring is an especially important supervisor function given that students rely very heavily on their PIs in guiding their research and providing career advice. As stated by a mechanical engineering PI in interviews conducted by the author, "[PhD] students do the research, I'm (...) the director and they're like the actors, actresses." As such, changes in mentoring could have strong implications for students' overall amount and quality of innovative output as well as subsequent career trajectories.

I examine this potential explanation using graduating students' responses provided to the research university's PhD exit survey. Data were only available

**Table 9.** Heterogeneity in PhD Productivity During the PhD Program (OLS Results)

During PhD (in log)	Patents		Publications	
	Amount (1)	Citation weighted (2)	Amount (3)	Highly cited (4)
Panel A: Basic <sup>a</sup>				
ePI (= 0/1)	0.116 (0.112)	0.150 (0.193)	−0.315*** (0.0611)	−0.369*** (0.0965)
Basic (= 0/1)	−0.217** (0.0738)	−0.284** (0.106)	−0.116 (0.328)	−0.0691 (0.238)
ePI × Basic	0.160 (0.252)	0.221 (0.374)	0.365* (0.202)	0.260 (0.263)
R <sup>2</sup>	0.271	0.272	0.402	0.376
Panel B: GRE				
ePI (= 0/1)	0.0983 (0.102)	0.126 (0.155)	−0.355*** (0.0791)	−0.418*** (0.103)
Aggregate GRE (≥324) (= 0/1)	−0.0352 (0.0358)	−0.0658 (0.0428)	−0.0924 (0.0619)	−0.123 (0.0866)
ePI × Aggregate GRE (≥324)	0.0800 (0.0629)	0.117 (0.110)	0.304* (0.151)	0.270 (0.187)
R <sup>2</sup>	0.275	0.275	0.412	0.384
Panel C: U.S. citizenship				
ePI (= 0/1)	0.178 (0.127)	0.229 (0.204)	−0.157* (0.0764)	−0.312** (0.140)
U.S. citizen (= 0/1)	0.0763* (0.0428)	0.0318 (0.0572)	0.0627 (0.103)	0.00737 (0.0821)
ePI × U.S. citizen	−0.140 (0.128)	−0.167 (0.193)	−0.273** (0.115)	−0.0594 (0.155)
R <sup>2</sup>	0.276	0.275	0.411	0.383
Panel D: Professor startup raised > \$USD 150K				
ePI (= 0/1)	−0.0162 (0.108)	−0.0609 (0.163)	−0.390** (0.147)	−0.499** (0.177)
ePI × >\$USD 150K	0.277* (0.154)	0.446 (0.259)	0.251 (0.280)	0.326 (0.209)
R <sup>2</sup>	0.277	0.277	0.411	0.384
Student controls	Yes	Yes	Yes	Yes
Professor, year, major fixed effects	Yes	Yes	Yes	Yes
Observations	2,536	2,536	2,536	2,536
Number of professors	434	434	434	434

Notes. This table displays the results from estimating Equation (2) and including interaction terms with an indicator equal one if a student ever worked for an entrepreneurial PI during the PhD. In Panel A, I interact ePI with an indicator equal to one if the PhD student was enrolled in a chemistry, biology, or textile sciences department (Basic). In Panel B, I include an interaction with having an incoming aggregate GRE above the 75th percentile (>324). In Panel C I include an interaction with an indicator equal to one if the student is a *U.S. citizen* at the time of the PhD. In Panel D, I include an interaction with an indicator equal to one if the startup the advisor founded received over \$USD 150K in funding (the median). Standard errors are reported in parentheses and are clustered on the professor and year level.

<sup>a</sup>In Panel A, major fixed effects are excluded.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

for student cohorts graduating from 2012 to 2016. Because this survey is part of the package students are asked to hand in before completion, response rates are very high (approximately 90% per cohort). The results are displayed in Table 10. I use the continuous exposure measure in this table to unveil heterogeneity in length of exposure. As displayed in Panel A, in terms of overall mentoring (column 1), availability (column 2), providing constructive feedback (column 3), and career support (column 4), students who worked for an entrepreneurial supervisor experience a 6- to 11-percentage-point decrease in the likelihood to give

their PIs a top score (five out of five) with increasing exposure. This also has consequences for the university as a whole. Students working for entrepreneurial PIs are less likely to respond with a top score to the question of whether they would still choose the university if they had to do graduate school again (column 5) and less likely to highly recommend the program to anyone considering pursuing a PhD (column 6). Panel B displays the results by years of exposure. The students who work under supervision of an entrepreneurial advisor the longest are the most likely to give their advisors a lower score. As displayed in

**Table 10.** Mentoring

Unit of analysis: Student	Exit survey responses					
	Mentoring score (=5)				Would (=5)	
	Overall (1)	Availability (2)	Constructive feedback (3)	Career support (4)	Still choose university (5)	Recommend program (6)
Panel A: continuous						
ePI (continuous)	−0.106*** (0.0136)	−0.0724*** (0.0114)	−0.107*** (0.0208)	−0.0634* (0.0270)	−0.0714** (0.0250)	−0.0757*** (0.0121)
R <sup>2</sup>	0.470	0.494	0.474	0.437	0.381	0.403
Panel B: By years of exposure						
ePI = 1	−0.131 (0.0788)	0.0601 (0.129)	−0.118 (0.0858)	0.0363 (0.0603)	0.0395 (0.143)	0.0924 (0.107)
ePI = 2	−0.324** (0.0850)	−0.0569 (0.141)	−0.450*** (0.0735)	−0.0476 (0.0883)	0.0439 (0.116)	−0.0102 (0.143)
ePI = 3	−0.226** (0.0560)	0.0420 (0.0464)	−0.298** (0.0670)	−0.0300 (0.118)	−0.0572 (0.0955)	−0.0688 (0.122)
ePI = 4	−0.418** (0.102)	−0.347** (0.114)	−0.586*** (0.0860)	−0.222** (0.0531)	−0.189 (0.116)	−0.128 (0.0774)
ePI = 5+	−0.511*** (0.0679)	−0.255*** (0.0367)	−0.504** (0.111)	−0.246* (0.114)	−0.295* (0.118)	−0.282*** (0.0607)
R <sup>2</sup>	0.472	0.499	0.479	0.438	0.382	0.405
Panel C: Continuous, controlling for advisor availability						
ePI (continuous)	−0.0552** (0.0189)		−0.0565 (0.0268)	−0.0214 (0.0219)	−0.0445 (0.0253)	−0.0448** (0.0110)
R <sup>2</sup>	0.714		0.714	0.603	0.449	0.492
Student controls	Yes	Yes	Yes	Yes	Yes	Yes
Major fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Professor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Graduation year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,020	1,020	1,020	1,020	1,020	1,020
Number of professors	274	274	274	274	274	274

*Notes.* This table displays the relationship between advising quality of professors as a function of entrepreneurial engagement. I report the results obtained from the university's PhD exit survey (only available for the years 2012 to 2016). The outcomes in columns 1–4 are equal to one if students gave their advisor a top score (five out of five). The dependent variable in columns 5 and 6 are responses to the questions whether students would still choose the university if they had to go to graduate school again, and whether they would recommend the program to someone wishing to pursue graduate school. Panel A displays the outcomes using the continuous measure of exposure; Panel B shows the results by years of exposure; Panel C is the equivalent of Panel A but including the advisor availability measure as a control. Standard errors are reported in parentheses and clustered on the graduation year level.

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\*  $p < 0.01$ .

Table A15 of the online appendix, using a more restrictive definition of *ePI* (student started at most five years after founding year), the results remain similar. When controlling for availability (Panel C), only results regarding the overall mentoring score and likelihood to recommend the program hold, and the coefficients are substantially reduced. This may indicate that a primary driver of perceived mentor quality is time, which may be more limited as advisors experience a shift in attention.

## 6. Discussion and Conclusion

The transfer of complex knowledge and skills is difficult, requiring face-to-face interaction, working side-by-side, and often years of coworking between a mentor and mentee. In this paper, I study a setting that embodies this type of learning, which is especially

critical to apprenticeship-like and on-the-job training: the academic laboratory. I thereby focus on the way a change in the attention of a PI, moving to entrepreneurship, influences knowledge transmission and skill development by examining the influence of this change on their PhD students' scientific productivity and careers.

My results, applying multiple estimation techniques, suggest that this relationship is negative for most outcomes and neutral or positive for some. Strikingly, my findings indicate that completing the PhD program under the supervision of an entrepreneurial PI is associated with a substantial decrease in the publication output of students. Depending on the model, the magnitude of this result lies between a 24.5% and 66.7% decrease for overall publications and between a 32.1% and 66.1% decrease for highly cited publication output students produce during PhD attainment. The

relationship with patenting output appears to be less conclusive and more neutral. In terms of careers, my analyses suggest that the PhD students trained by an entrepreneurial advisor experience a decrease in the likelihood of assuming a faculty position, which is accompanied with a decrease in the likelihood of joining a small firm and an increase in the likelihood of starting a consulting job for those students who embark on the private-sector career trajectory on graduation. Taking a deeper look into potential mechanisms, I do not find support that life cycle trends, changes in funding, or changes in the composition of incoming student cohorts are the main drivers of my results, although they may explain some of the variation. The inclusion of proxies and controls for these factors suggests that my baseline estimates may present a possible lower bound, especially for average students and those enrolled in engineering programs. In turn, by examining authorship patterns, the impact, and direction of research, as well as by exploiting field, student quality, and citizenship differences, my results seem to indicate that the most feasible explanation lies in the reduction of student development rather than changes in research orientation.

This study is not without limitations, especially provided the sampling technique I chose (Perkmann et al. 2013). The disadvantages of using one research university only are generalizability and potential organization bias introduced by idiosyncrasies of the institution I examine. It could be that the professors and students of this R1 university are more or less susceptible to the side effects of entrepreneurial engagement than those of other universities, given differences in the type of individuals who work and attend this university, the structures in place for supporting entrepreneurship, and the general environment. There are, however, several reasons I believe my context, although unique in some ways, can apply to other similar U.S. elite research institutions. For example, the research university I examine is among the top research universities and public colleges in the United States. In 2017, it ranked among the top 25 doctorate-granting institutions by number of doctorate recipients (National Science Foundation 2018), and in 2019, all of its PhD programs in the fields of engineering and computer sciences ranked among the top 10 in the country in terms of reputation. Given its high standing as an innovative research institution, it is a likely destination for the relevant population both in terms of faculty and students. Furthermore, the school's business incubators are ranked within the top 20 in the United States, one of which is among the oldest in the country. This existing support system should make transitioning into entrepreneurship easier and should reduce professors' constraints relative to other universities (rankings and numbers from university website).

Moreover, one feature of my study, but also a potential limitation, is that I focus my attention on examining what happens when advisors become entrepreneurial in the first place rather than become more entrepreneurial over time. As such, my study can provide insight on the extensive margin of entrepreneurial activity, the transition into entrepreneurship, but is restricted in the extent to which it can inform us about the intensive margin of entrepreneurial activity. An examination of the latter may be a fruitful area for follow-on research.

Although primarily correlational, my findings contribute crucially to the current discourse on the incentives of promoting academic entrepreneurship (Bouwma-Gearhart et al. 2020) and highlight the potential trade-off between two different channels of knowledge transfer from universities to private firms. One is through the creation of university spinoffs, whereas the other is embodied by students. I further detect potential decreases in public returns to science and changes in private returns to pursuing the PhD, given a reduction in the amount and impact of public knowledge emanating from the labs of entrepreneurial advisors, decreases in student satisfaction, and a reduction in the likelihood of PhD students becoming faculty themselves. My finding that PhD students are more likely to pursue a job at a consulting firm on graduation points to a possible positive consequence, namely a potential strengthening of a channel that enables the transfer of general scientific skills and cutting-edge knowledge to a larger number of firms in the private sector.

This article also opens several promising avenues for research. First, my study extends prior work on the potential side effects of entrepreneurship/commercial activity by examining how this is associated with PhD student productivity and careers. The focus is, however, only on a selection of possible PhD student outcomes. To get a better understanding of how to structure incentive schemes around academic entrepreneurship, more research assessing other outcomes and the associated tradeoffs is needed. Second, because entrepreneurial professors are generally those professors who perform best, this also opens up further questions with regard to the role of entrepreneurial ability in explaining a successful academic career. Third, related to this research, it is fundamental to understand whether allowing and providing employees incentives to engage in entrepreneurship is necessary for personnel retention. It may well be that without this type of freedom the most productive employees will leave altogether, lured, for example, by higher pay or new challenges (Toole and Czarnitzki 2010, Campbell et al. 2012). Especially in "hot" fields where human capital is in high demand, university professors may become more susceptible to joining the private sector, which has been suggested to

have an important negative impact on innovation (Gofman and Jin 2019). One prominent example is the case of Uber and the National Robotics Engineering Centre at Carnegie Mellon University. In 2015, 40 of the center's 140 staff members left to join the taxi-hailing company (*The Economist* 2016). Fourth, because I examine only one research university in this paper, future research that extends these findings to other institutions, settings, or countries may provide additional important insights.

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## Endnotes

<sup>1</sup> In the United States, the academic sector is the largest producer of science and engineering publications, having accounted for 75.2% of U.S. science and engineering publication output in 2016. In 2015 alone, a total of 55,000 doctorate degrees were awarded in science and engineering disciplines across universities in the United States (National Science Board 2018).

<sup>2</sup> Working as research assistants in labs is the predominant way PhDs fund their graduate studies in the sciences and engineering. Taking numbers from the 2016 Survey of Earned Doctorates, roughly 80% of all doctoral recipients in engineering were funded by research assistance or research grants (National Science Board 2018). The remaining 20% were teaching assistants or relied on other sources of funding.

<sup>3</sup> Between 1997 and 2017, on average (weighted by number of recipients per field and year), 53% of newly minted PhDs in the life sciences (29%), computer sciences (50%), and engineering (73%) went on to pursue a job in industry on graduation (National Science Foundation 2018).

<sup>4</sup> I include only those startups that are clearly based on technologies. Examples include robotic hands, therapeutic products for preventing nerve damage, autonomous vehicle testing, and intravenous three-dimensional imaging.

<sup>5</sup> One form of commercialization is patenting, a legal mechanism by which a governmental entity gives inventors the right to exclude others from using their invention and appropriate private value from such invention in the form of, for example, licensing fees. In the context of academia, most patents are based on the research produced in labs and are often a side product of an existing research agenda (Azoulay et al. 2007). Another form of commercialization is entrepreneurship, which entails creating a company around a specific idea and/or technology and implies a much more active commercialization intent. There are important nuances when it comes to founding. Academic founders can assume different roles in their companies, such as advisory or executive positions. The main distinction lies in the level of involvement in daily operations (Stuart and Ding 2006). Whereas founders with advisory roles give guidance to the board and executive officers of a startup, founders assuming an executive role take on more responsibility and stewardship of running the company (Conti and Roche 2021).

<sup>6</sup> Although I have information on students and professors in the department of biology, I exclude these professors from my analyses because only one professor was ever a founder. Students majoring in biology are still included in my sample.

<sup>7</sup> In the online appendix, Figure A1 displays the innovative output of professors at the research university I examine. Over time, although there has been variation in the range of publication and patenting output of individual professors, the university average has remained stable. The university I examine has consistently ranked nationally among the top five most innovative public (top 20 overall) research universities (<https://www.reuters.com/article/us-amers-reuters-ranking-innovative-univ/reuters-top-100-the-worlds-most-innovative-universities-2017-idUSKCN1C209R>).

<sup>8</sup> The author developed a Python script that provided a list of all possible matches based on observable information. If there was more than one match, the author (and research assistants) manually looked up the individual and read through the corresponding author descriptions and additional web information to identify the correct individual. I was unable to retrieve publication information for four professors, none of which were ever entrepreneurs. For the patent records, given that the assignee of the patents is the university, this facilitated the search.

<sup>9</sup> The number of professor founders and startups emanating from the university are comparable to similarly ranked public universities (sources: Crunchbase and private VC information).

<sup>10</sup> In the online appendix, Figure A2, I report the distribution of number of startups per founder.

<sup>11</sup> My findings are robust to using different log transformations such as the inverse hyperbolic sine (IHS) transformation of each outcome ( $\ln(I_{s,p,m,t} + ((I_{s,p,m,t}^2 + 1)^{0.5}))$ ) or  $\log(x + 1)$ .

<sup>12</sup> I was unable to retrieve the publication output of 275 students. This may be because they never published or because of difficulties with name disambiguation.

<sup>13</sup> I define publications as highly cited if the citation count of a publication (including articles and conference proceedings) is above the median of the type of publication published at the same department in the same year.

<sup>14</sup> I use the data provided from the PhD exit survey for publications (the responses range from no publications to 10 or more) and cross-validate this with the information collected using Scopus. The numbers are similar and the correlation >0.5.

<sup>15</sup> Please refer to online appendix, Table A2, for a comparison of students by type of PI and to Table A3 for summary statistics of all professors and all professors with at least one patent or who are founders.

<sup>16</sup> For a breakdown of these majors please refer to Table A8 of the online appendix.

<sup>17</sup> Anecdotal evidence from interviews suggests that these are not factors that advisors consider when selecting students.

<sup>18</sup> I measure PhD student outcomes using a five-year time window from entering the PhD program, which represents the average and median PhD duration and accounts for publication time lags. These patterns are similar across doctorate degree-granting institutions in the United States (National Science Foundation 2018). I provide a graph in the online appendix, Figure A3, displaying the distribution of PhD duration at the focal university.

<sup>19</sup> Binned scatter plots presented in the online appendix, Figure A4, provide support that the publication output results are not driven by outliers. With regard to patents, there is reason to believe that a few large positive outliers may be responsible for the positive coefficient.

<sup>20</sup> In the online appendix, Table A6, I report the results from using a different definition of entrepreneurial engagement. Namely, I only set *ePI* to one if the student entered the program at the most within five years of the professors starting a company. The results remain similar.

<sup>21</sup> At the examined institution, tenured professors are those that have achieved the rank of associate or full professor. In the model displayed in Table A7, I interact *ePI* with an indicator equal to one if the advisor was a full professor at the time of a student's entry and zero otherwise.

<sup>22</sup> In further results left unreported, I examine the impact of entrepreneurial engagement on a professor's best performing student. The directionality and magnitude of the result is similar to the average.

<sup>23</sup> In results left unreported, I compare the characteristics of students of entrepreneurial PIs who complete the PhD and those who dropout. The only detectable differences I find are with regard to students' ethnicity. Those who drop out are less likely to be Asian. For further robustness, I apply an alternative approach to examine whether students' characteristics change with PIs' entrepreneurial engagement. Following the logic of two-sided matching approaches (Mindruta 2013), I create all pair-wise combinations of students and professors who were present at entry of a student in the student's advisor's department. I include all students entering a PhD program regardless of whether they finish or not, leading to an overall sample of 330,469 pairs. The results suggest that matching on the observables I include does not seem to be taking place. These results are displayed in the online appendix, Figure A5 and Table A9.

<sup>24</sup> I further visually examine whether there are any changes in the academic quality, nationality, and prior work experience of students before and after a professor becomes an entrepreneur. To determine this, I again use GRE scores, previous GPAs, the quality of a student's previous degree-granting institution, U.S. citizenship, previous work experience, and having a pre-PhD publication record as proxies for incoming students' quality and characteristics. Here, I restrict my analyses to students of entrepreneurial advisors only. I further include professor, major, and year fixed effects, and I control for major-year trends. I cluster robust standard errors on the advisor level. The results, in the online appendix, Figure A6, depict little evidence that students differ substantially in terms of their GRE scores, previous GPAs, quality of previous degree-granting institution, previous work experience, or pre-PhD publications record before or after a PI transition into entrepreneurship.

<sup>25</sup> In the online appendix, Table A12, I report the results from including the homophily related controls suggested by Azoulay et al. (2017) in the matching model presenting in Table 4. I further include the results for students joining from all other institutions other than the PhD degree granting one in columns 5 and 6.

<sup>26</sup> The number of observations drops given that all cohorts graduating in 2017 have zero postgraduation outcomes. In results left unreported, I restrict the sample to student who graduate by 2012, and the directionality of the results in the same and the magnitude is stronger.

<sup>27</sup> Generally, on graduation in science and engineering fields, PhDs have three broad choices of employment type: academia, industry, and national labs/government. The positions they pursue include working as R&D scientists or as consultants in industry, or as faculty, research technicians or postdocs in academia. Typically, the postdoc is viewed as a necessary step toward becoming faculty in science and engineering areas (although there are important field differences and starting as faculty is possible) and can be completed at a host of different research institutions including national labs. Taking numbers from the 2016 Survey of Earned Doctorates, roughly 14% of engineering graduates (30% computer science (CS) and mathematics graduates) who had plans to stay in the U.S. after graduation reported definite nonpostdoctoral academic employment commitments, whereas 35% (30% CS and mathematics graduates) reported commitments to pursue a postdoc (National Science Board 2018). The type of position a PhD obtains also has important implications for their salaries. Again using information from the 2016 Survey of Earned Doctorates, the median basic annual salary of a newly minted PhD graduate in engineering (CS) was around USD\$100,000 (USD\$122,000) in industry, approximately USD\$80,000 (USD\$70,000) in academia, and in the vicinity of USD\$47,000 (USD\$59,000) as a postdoc (National Science Board 2018).

<sup>28</sup> Anckaert et al. (2020) find that following the model developed by Boyack et al. (2014) reveals similar results to the CHI classification.

<sup>29</sup> Recently, concerns have been voiced about the predictive power of the GRE test scores, leading some graduate programs to drop them as entry requirements (Langin 2019). In the online appendix, Table A10, Panel B, I report the results from an interaction with an incoming GPA within the 75th percentile. Here, I find similar patterns to those using the GRE scores.

<sup>30</sup> As an additional test, I ran the same model, but using students with a European Union citizenship who, relatively speaking, should have a very high bar to pass to pursue a PhD in the United States. The results flip as expected.

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