Artificial Intelligence, Human Capital, and Innovation*

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Abstract

Human capital is essential to AI-driven innovation. The scarcity of the human capital needed for AI R&D created an unprecedented brain drain of AI professors from North American universities into the industry between 2004 and 2018. We provide a causal evidence that AI faculty departures from universities reduced the creation of startups by students who then graduated from these universities. On the intensive margin, these departures also reduce the early-stage funding graduates' startups receive. The disruption in the knowledge transfer from professors to students emerges as the main channel for the negative effect of the human capital reallocation for innovation.

Keywords: Artificial intelligence, deep learning, human capital, innovations, entrepreneurship, education

JEL classification: L26, O33, O31, I23, J24

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1 Introduction

Highly specialized human capital is a scarce resource that can be used either for innovation of products and services or for educating future innovators (e.g., Nelson 1959; Arrow 1962). This trade-off is particularly important for artificial intelligence (AI) which is considered to be an emerging general purpose technology that has a potential to transform many industries.[1]

In the last decade, the emergence of deep learning algorithms, GPU computing, and Big Data resulted in a Big Bang for AI applications.[2] Significant breakthroughs took place in image recognition, natural language processing, self-driving cars, drug discovery, genomics, robotics, and more. These innovations have a potential to change the economy and the society.

The adoption of AI by corporations has been growing since 2012, when AlexNet deep neural network won an international image classification competition, ImageNet, by a significant margin (Gershgorn 2018). As a sign of AI's increasing importance, the 2018 Turing Award, which considered the Nobel Prize of computing, was given to three researchers who laid the foundations for the current AI boom (Metz 2019).[3]

As AI becomes one of the most promising and disruptive technologies (Acemoglu and Restrepo 2018), the top tech firms are trying to corner the market for AI talent, especially AI professors. Two of the three 2018 Turing Award winners, Geoffrey Hinton and Yann LeCun, were hired by Google and Facebook to lead their AI projects respectively. When AI professors leave academia, a new generation of AI entrepreneurs are not able to innovate using some of the most promising general purpose technologies of our times. These innovations are important as they have a potential to change every aspect of our lives and spur economic growth.

Despite lots of public interest in the brain drain of AI professors to the industry (Lowensohn 2015; The Economist 2016; Sample 2017; Spice 2018; Procaccia 2019), there is no study that

[1] AI mainly consists of six disciplines: natural language processing, knowledge representation, automated reasoning, machine learning, computer vision, and robotics (Russell and Norvig 2016).

[2] Deep learning is a machine-learning technique that uses neural networks with a very large number of layers (LeCun, Bengio, and Hinton 2015). GPU computing refers to graphic processing units that allow high parallelization of computations relative to the standard CPU computing.

[3] Alan Turing is considered the father of AI. Almost 70 years ago, he both proposed the famous Turing test and correctly predicted the machine learning techniques used today (see Turing 1950).

systematically investigates this issue.[4] Thus, our first contribution is to use a hand-collected dataset of AI faculty departures to document the brain drain of AI professors from universities into the industry. The number of AI professors at North American universities leaving academia for an industry job has increased exponentially since 2009 (see Figure 1). Prior to 2010, only a few tenure-track or tenured AI professors left academic positions for an industry job, but in 2018, almost 40 faculty did so. In total, we identify 180 AI faculty from North American universities who accepted an industry job from 2004-2018. In addition, there are 41 professors who founded AI startups either while employed at universities or after leaving academia. Together, our sample includes 221 faculty, who either accepted an industry job from a private company or founded their own startup. We also identify 160 AI faculty who moved to another North American university during the same period. The fact that more faculty left for the industry than for another university is one of the signs that the brain drain of AI professors to the industry is unprecedented.[5]

To induce the best AI professors to leave their tenure-track or tenured positions, the industry offers them millions of dollars in compensation (e.g., Metz 2017, 2018a). The corporate poaching of AI faculty has raised public concerns about its negative impact on universities (e.g., The Economist 2016; Sample 2017). "That raises significant issues for universities and governments. They also need A.I. expertise, both to teach the next generation of researchers and to put these technologies into practice in everything from the military to drug discovery. But they could never match the salaries being paid in the private sector." said Yoshua Bengio, one of the 2018 Turing Award winners and a professor at the University of Montreal (Metz 2017). In a recent Bloomberg op-ed, Ariel Procaccia, an associate professor of computer science at CMU, says "If industry keeps hiring the cutting-edge scholars, who will train the next generation of innovators in artificial intelligence?" (Procaccia 2019).

Our main contribution is to study the effect of AI faculty departures on the real economy. In

[4] Usually the term "brain drain" is used in the context of immigration of highly skilled works to another country (Kwok and Leland 1982), in this paper we use this term to describe the exodus of AI professors to the industry. In section 4.2, we discuss the potential implications of our findings for the brain drain in the international context.

[5] Azoulay, Ganguli, and Zivin (2017) document that for every life scientist who left for an industry job from 1977 to 2006, 90 moved to another department in academia.

particular, we focus on startups incorporated by students who had been affected by faculty departures. If faculty departures reduce entrepreneurship by the alumni, the brain drain can have significant implications on innovation, the rate of creative destruction, and economic growth (Schumpeter 1942). The main hypothesis is that faculty departures to the industry reduce the knowledge transfer to the students. As a result, we should expect a reduction in students' innovation after graduation both on the extensive and the intensive margins.

To test this hypothesis, we study the sample of 363 AI entrepreneurs who graduated from 69 North American universities between 2010 and 2018 and who established AI startups after the graduation. These startups innovate in the areas of cyber security, retail, breast cancer early detection, solutions for the oil and gas industry, augmented reality, sleep therapy, supply chain planning, and more. Interestingly, none of these startups was established by graduates of an university that does not have AI faculty, suggesting that the AI knowledge acquired at institutions of higher education is a critical determinant of AI startup formation. Moreover, 24% of AI startups have at least one founder with a PhD degree, which is more than three times higher than for non-AI startups in the Information Technology (IT) field. In addition to having more educated founders, AI startups on average raise \$1.01 million more in the first round and \$2.9 million more in the second round than the funding raised by other types of startups in IT field.

On the extensive margin, we find that AI faculty departures have a negative effect on the AI startups of students who graduated from the the professors' former universities. In particular, we find that the departures by tenured professors' 4-6 years prior to the students' graduation year have the largest effect. Specifically, for a given university, a one standard deviation increase in tenured professors' departures during time window $[t-6, t-4]$ on average reduces the number of future AI entrepreneurs who graduate in year t by 13%. At the individual level, our analysis shows that tenured AI professors' departures in time window $[t-6, t-4]$ significantly decreases a STEM graduate's probability of becoming an AI entrepreneur. The effect is most pronounced for the top 10 universities, entrepreneurs with PhD degrees, and for startups in the field of deep learning. More recent departures (i.e., one to three years prior to the entrepreneur's graduation) do not have a significant effect, consistent with the knowledge transfer explanation for the negative effect and inconsistent with the explanation that students prefer to join professors' R&D groups at companies rather than establishing their own startups. Overall, both university-level and individual-level analyses suggest that the brain drain of tenured AI professors into the industry affects indirect innovation, as measured by the number of new AI startups. We also find that when tenured AI professors leave universities and they are replaced by faculty from lower ranked schools, the negative effect of the faculty departures on AI startups intensifies. That further confirms that knowledge transfer is the main economic channel for the negative effect of the AI brain drain from universities on innovations by students.

On the intensive margin, we find that AI faculty departures have a negative effect on the early-stage funding of AI startups with founders who graduated from the affected universities.[6] Specifically, a one standard deviation increase in the tenured professors' departures in time window $[t-6,t-4]$ decreases, on average, first round and series-A round funding by, respectively, \$0.6 million and \$3.15 million. Relative to the sample average, these numbers imply an 22% decrease in first-round funding and a 28% decline in series-A-round funding. Moreover, a one standard deviation increase in the tenured professors' departures in time window $[t-6,t-4]$ decreases funding growth from the first round to the second round by 20%.

One potential endogeneity issue is that local unobservable factors, such as closure of a VC office/incubator, drive both AI faculty departures and the reduction in startups. To address this concern, we instrument AI faculty departures with the average number of citations of the AI professors at a given university for each year. A high number of citations is likely to attract more industry attention and interest but is highly unlikely to be driven by any unobservable local factors that reduce the number and the funding of AI startups more than four years later. We find that average number of citations for AI professors at a university strongly predicts whether the university experiences above median departures. The results from the 2SLS regression are consistent with previous results. Moreover, we do not find a reduction in AI startups in the same city but with

[6] Our focus is on early stage startups because as of year 2018, 85% of the AI startups in our sample are still in the early stage (i.e., no later than series A round).

entrepreneurs who graduated from non-local universities. These results point towards the causal effect of the departures, and are not consistent with the explanation that local factors affect both the departures and the startups.

The negative effects on AI startups due to AI faculty departures from a given university could be offset by an increase in AI startups at other universities or an increase in other types of startups in the field of IT, suggesting that the negative effect on startups may not exist at the aggregate level. We find that the number of non-AI startups in the IT sector by graduates of the affected universities does not increase. We also find that AI faculty departures in one university do not increase the number of AI startups by graduates of other universities that are similarly ranked or are in the same geographic area. Together, these results suggest that AI faculty departures negatively affect the total number of AI startups by graduates, not just pushing AI entrepreneurs to become non-AI entrepreneurs or to pursue AI studies at other universities. The implication is that the knowledge transfer reduction has an aggregate effect on innovations by university graduates, rather than just a redistributional effect.

Related Literature. The recent exponential growth in AI applications has drawn much public attention, but the academic research about AI's impact on the economy and the society is still emerging. In a recent paper, Acemoglu and Restrepo (2018) develop a framework in which AI can have both a negative and a positive effect on demand for labor. The negative effect is due to the displacement risk, and the positive effect is due to improved productivity and higher capital accumulation. Korinek and Stiglitz (2017) and Guerreiro, Rebelo, and Teles (2017) discuss the channels through which AI can increase inequality and the best way to address this concern. Aghion, Jones, and Jones (2017) study the implications of AI on economic growth. Our analysis complements this research by studying the interplay between AI knowledge diffusion, human capital, and innovation. We show that the reallocation of human capital from academia to the industry deteriorates the transfer of AI knowledge from professors to future innovators. To the best of our knowledge, we are the first to show that faculty departures have a large negative causal effect on the quantity and quality of innovation by students.

The paper also contributes to the literature that studies how scientific discoveries transform an industry or create a new one. Zucker, Darby, and Brewer (1998) study the emergence of the biotech industry as a consequence of the 1973 discovery of recombinant-DNA by Stanley Cohen and Herbert Boyer. They find that the locations where scientists worked in this field in the 1980s can explain the locations of biotech firms in the US ten years later. They argue that the agglomeration effect exists because only a few star scientists were willing to leave academia and were instead working on the commercialization of the technology while employed by their universities.[7] We find that an unprecedented number of AI professors is willing to leave academia. Given that AI technology has the potential to transform not a single industry, but the whole economy (Brynjolfsson, Rock, and Syverson 2017; Trajtenberg 2018; Cockburn, Henderson, and Stern 2018), the effect of the brain drain goes beyond a single industry. That could also explain why AI faculty departures have such a large economic impact on the number of startups and on the early-stage funding.

Our paper also contribute to the debate about the role of the specialized training versus generalist training for entrepreneurship. Lazear (2004; 2005) provides a theoretical model and empirical evidence based on Stanford MBA graduates and shows that a university's generalist, rather than specialist, training is a more important determinant of its graduates' entrepreneurship. Our study shows that for breakthrough technologies, such as AI, specialist training is crucial for students' ability to become entrepreneurs and to get early stage funding.[8]

More broadly, our paper is related to entrepreneurial financing and economic growth literature. Bernstein, Korteweg, and Laws (2017) design a randomized field experiment showing that information about the human capital of a founding team is a major determinant in attracting early-stage investors. We complement their study by providing evidence that faculty departures limit the transfer of AI knowledge from professors to future founders, which in turn leads to less early-stage

[7] Jaffe (1989) documents the positive impact of university research on commercial patent filings and R&D investment by local corporations.

[8] AI entrepreneurs who are negatively affected by the brain drain of AI professors are not more likely to have MBA co-founders (see Table OA1 in the Online Appendix). It suggests that the knowledge that MBAs receive in a business school is a not a substitute for the knowledge provided by AI professors.

funding for the founders' startups. In terms of economic growth, Samila and Sorenson (2011) and Glaeser, Kerr, and Kerr (2015) document the positive causal effect of the number of startups on economic growth. The exponential growth in AI faculty departures is therefore especially concerning because the already large negative effect of faculty departures on the number of startups has a lag of approximately six years.

2 Data Description and Summary Statistics

2.1 Data Collection

Our analysis combines data from LinkedIn, CSRanking.com, CrunchBase, and Google Scholar.

For AI professors leaving for an industry job, we exploit a hand-collected sample from LinkedIn. To obtain AI professors from LinkedIn, we employ two searching processes. The first involves directly searching in Google with inputs such as: site:linkedin.com/in/ "Professor" and "Artificial Intelligence"[9], which allows us to retrieve all the LinkedIn profiles returned by Google.

Our second method is to search in LinkedIn using reviewers' and program committee members' names of AI related conferences. We picked three of the most prestigious conferences in the field of machine learning and artificial intelligence[10] and extracted the names of reviewers and committee members from 2008 to 2018. Because there are also reviewers and committee members from the industry, this procedure includes faculty who left academia for the industry. We manually check each person's LinkedIn page and sometimes their academic webpage to verify the results.

As we only consider tenured or tenure-track faculty, we exclude from the sample people with titles like "Adjunct Professor", "Clinical Professor ", and "Research Professor". We classify assistant professors as tenure-track faculty and associate or full professors as tenured faculty.[11] The

[9] Another example of a search input is: site:linkedin.com/in/ "Professor" and "Deep Learning" . In general, we search for professors who mention one of the subfields of AI, such as natural language processing or autonomous driving, on their LinkedIn profiles.

[10] The three conferences are the International Conference on Machine Learning (ICML), Neural Information Processing Systems (NeurIPS), and the Association for the Advancement of Artificial Intelligence (AAAI).

[11] Some universities might have untenured associate professor positions. Unfortunately, we are not able to infer these cases based on the information posted on LinkedIn. It is unlikely that the potential misclassification of associate

final sample includes 221 tenure-track and tenured AI faculty in North American universities who posted that they took a position in a private company between 2004 and 2018.[12] Figure 1 shows the aggregate time trend. We also identify 160 tenure-track or tenured faculty who moved within North American academia. In our empirical analysis, we use both the faculty who leave to industry and to another university.

We also hand-collect data on faculty size at the top 100 universities' computer science departments from CSRankings.org, which provides the number of full-time, tenure-track and tenured CS faculty for each year based on data from DBLP.[13] DBLP provides open bibliographic information on major computer science journals and proceedings. Its website states that "DBLP indexes over 4.4 million publications, published by more than 2.2 million authors. To this end, DBLP indexes about 40,000 journal volumes, more than 39,000 conference and workshop proceedings, and more than 80,000 monographs."[14]

Entrepreneurs' and startups' information is based on a sample from the CrunchBase database.[15] According to the Kauffman Foundation, CrunchBase is "the premier data asset on the tech/startup world."[16]

CrunchBase includes university graduates who are not only founders of AI startups. We use information about all the graduates (founders and non-founders) to study how AI faculty departures affect student's probability to become a founder of an AI startup after graduation. The sample we obtain from CrunchBase includes about 3,000 STEM alumni who graduated from North American universities during 2010 - 2018 and about 177 AI startups and 591 IT startups whose founders graduated from North American universities during 2010 - 2018.

To classify AI entrepreneurs/startups, we rely on the business categories CrunchBase provides. AI entrepreneurs/startups have at least one of the following categories: artificial intelligence, ma-

professors has any qualitative effect on our results.

[12]Our sample can underreport the actual number of AI faculty departures to industry because some professors might not have LinkedIn accounts or leave their LinkedIn profiles out-of-date.

[13]See http://csrankings.org/faq for detailed information about CSRankings.org.

[14]Source: https://dblp.org/faq.

[15]CrunchBase would be a less than ideal database for studying entrepreneurship in non-tech industries, but for our study, the database's tech industry focus works to our advantage.

[16]Source: https://www.kauffman.org/microsites/state-of-the-field/topics/finance/equity/venture-capital

chine learning, deep learning, neural networks, robotics, face recognition, image processing, computer vision, speech recognition, natural language processing, autonomous driving, autonomous vehicle, and the semantic web.

Last, we hand-collected from Google Scholar the citation data of AI faculty, which are used as a proxy for the quality of their research. We use citations to predict faculty departures in the first stage, and then we use these predicted departures in the second stage to study their effect on students' innovation.

2.2 The Brain Drain of AI Professors to the Industry

As AI-driven solutions help firms from all industries to address previously unsolvable business problems, companies are trying to poach AI professors from universities. In February 2015, Uber began a strategic partnership with Carnegie Mellon University (CMU) to work on autonomous driving. Four months later, Uber hired about 50 people from CMU, which was termed "a partnership based on poaching" (Lowensohn 2015).

We systematically investigate this brain drain and identify 221 tenured and tenure-track AI faculty who left academia for a full-time industry job between 2004 and 2018. Figure 1 shows an exponential trend in the number of faculty departures. In our sample, there was no AI professor who left for an industry job in 2004 whereas 39 AI professors did so in 2018. Figure 1 also shows the citation ratio of AI faculty who left for an industry job to all AI faculty. For each year and each university, the citation ratio is calculated using the sum of citations from faculty who left for an industry job (stock at the time of departure) divided by the sum of citations from all AI faculty in this university; we then average across universities to get a proportion of citations for a given year. Only 4% of total AI citations from a university are from professors who left for the industry in 2010, on average, whereas AI professors who left academia for an industry job in 2018 account for about 20% of a university's total AI citations.

Figure 2 considers further whether there is any difference between the departures of tenured faculty and untenured faculty for an industry job. We see that the two groups of faculty members exhibit similar trends. Figure 2 also depicts a rapid growth in AI faculty size from 2004 to 2018 for the top 100 North American universities, ranked by CSRankings.org. In 2004, the average faculty size for those universities was about 3.5, while in 2018, average AI faculty size increased by almost 80%.

Figure 3 shows the top 18 North American universities in terms of the number of faculty lost from 2004 to 2018. The three universities that lost the most AI faculty are Carnegie Mellon University (CMU), the University of Washington, and UC Berkeley. CMU lost 17 tenured faculty members and no untenured faculty, and the University of Washington lost 7 tenured and 4 assistant professors. For Canadian universities in our sample, the University of Toronto lost the most AI professors, 6 tenured faculty and 3 assistant professors.

Figure 4 presents firms that hired most of the AI professors. In our sample, Google, Amazon, and Microsoft poached the most AI professors from North American universities. From 2004 to 2018, Google and its subsidiary, DeepMind, together hired 23 tenure-track and tenured AI professors from North American universities. Amazon and Microsoft respectively hired 17 and 13 AI professors. Apart from technology firms, we also see that large firms from the finance industry poach AI professors, such as Morgan Stanley, American Express, and JP Morgan. It is worth noting that that these publicly traded firms hired about 45% of 221 professors who accepted an industry job in our sample.

2.3 Competition for AI Talent

Although the compensation data that AI professors receive from industry positions is not publicly available, anecdotal evidence may provide a sense about how large the pay gap is. Ilya Sutskever, Geoffrey Hinton's student, went to work for OpenAI in 2016, a non-profit organization that aims to democratize AI, where he was paid more than $1.9 million dollars that year. "I turned down offers for multiple times the dollar amount I accepted at OpenAI. Others did the same." Mr. Sutskever said (Metz 2018a).[17] As a comparison, the highest paid AI professor at UC Berkeley received \$430,196 in 2017.[18] The large pay gap between industry and academia makes it virtually impossible for universities to retain their best AI professors.[19]

One of the reasons for the pay gap is that universities do not capture returns on the highly valuable human capital that students gain by learning from AI professors (Rothschild and White 1995). Figure OA1 in the online appendix shows a difference in the median wages between work visa (H1B) applicants who are software engineers with AI skills versus general software engineers. The difference did not exist in 2010, it started to grow in 2011. In 2018, the difference was 20,000 USD, which is more than 15% premium. The AI wage difference exists both at the bachelor and the master levels. Despite that the returns on human capital specialized in AI are higher, the universities do not hold "equity" in students' human capital to capture this premium. Moreover, if students use their university-acquired knowledge to establish successful AI startups, the university does not gain from this entrepreneurship activity of its students either. Even if a university could capture the increased returns on AI human capital of its students, the structure of the compensation system at the university could prevent it from paying AI professors risk-adjusted industry-level salaries.

In this paper, we take as given the frictions that prevent universities to compete with the industry and study the consequences of the brain drain of AI professors on AI startups by students at the affected universities.

3 Empirical Analysis

This section presents empirical evidence of how AI faculty's departures to industry affect AI startups by university graduates. We start with comparing the characteristics of AI startups and AI

[17] "Well-known names in the A.I. field have received compensation in salary and shares in a company's stock that total single- or double-digit millions over a four- or five-year period." (Metz 2017). See also Metz (2018b).

[18] The wage data is from https://ucannualwage.ucop.edu/wage/

[19] In addition to higher pay, industry positions can offer better computational resources and access to the commercial datasets needed to train AI algorithms.

entrepreneurs with those of startups and entrepreneurs in other fields of IT, and conclude that AI startups require higher level of expertise and knowledge than startups in non-AI fields of IT. We then show that, four to six years after the departures of tenured AI faculty, graduates are less likely to become AI entrepreneurs (extensive margin) and receive less early-stage funding for their AI startups (intensive margin). Moreover, using average AI faculty citation at university level as an instrumental variable, we argue that the negative effects on the both extensive margin and intensive margin are causal. We also study the ability of universities to replace the departing faculty, and the effect of the departures have on entrepreneurship at other universities.

3.1 AI Startups and AI Entrepreneurs

The rapid development of AI applications has spurred AI startup activities in the US with a record funding of \$9.33 billion from VC firms in 2018, comprising almost 10% of all VC funding for that year (Su 2019). Despite the almost tenfold growth in funding for AI startups from 2003 to 2018, little is known about the characteristics of these startups and factors affecting their formation (PWC 2018).

In Table 2, we compare characteristics of 363 AI entrepreneurs from 177 AI startups that were founded by graduates who graduated during 2010 - 2018 with characteristics of 985 entrepreneurs from 591 IT startups that are not AI and were founded by graduates who graduated during the same period.[20] We find that the distribution of the educational levels for AI founders is skewed towards higher degrees. Specifically, 24% of AI startups have at least one founder with a PhD degree, while only 7% of other startups in the IT field have at least one PhD-holding founder. In terms of early-stage funding, compared to other IT startups, AI startups raised \$1.01 million more in the first round and \$2.9 million more in the series A round.

We find that AI entrepreneurs[21], on average, hold a higher academic degrees than non-AI entrepreneurs, with as many as 26% holding a PhD degree, as opposed to 10% for non-AI en-

[20] Some of these AI and non-AI startups also have co-founders who graduated before 2010. And we do not include those who graduated before 2010 in our founder sample.

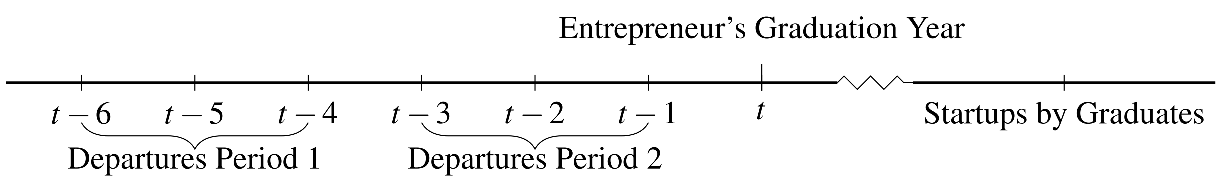
[21] An AI entrepreneur is identified if he or she starts an AI startup in our sample.

trepreneurs. AI entrepreneurs are less likely to be the sole founder relative to non-AI entrepreneurs. They also have a larger time gap between the graduation year for their highest degree and the year when they established their startup. All these facts suggest that AI startups require a higher level of expertise and knowledge than do startups in non-AI fields.

Figure 5 shows the North American universities that produced the most alumni who established AI startups after receiving their highest degree. In our sample, 77 MIT graduates and 72 Stanford graduates established AI startups. Carnegie Mellon University, ranked 3rd in terms of producing AI entrepreneurs, produced 39 AI entrepreneurs. The Canadian university with the most AI entrepreneur alumni is the University of Waterloo, at 21 such graduates.

The above analysis shows that high quality university education is especially important for AI entrepreneurs. AI professors play a very important role in providing this education. We proceed to study the effect of the brain drain of AI professors on entrepreneurship.

3.2 Empirical Design



This figure plots the timeline for our empirical design. For departures, we focus on tenure-track and tenured AI professors who left academia for an industry job in two time windows, $[t-6, t-4]$ and $[t-3, t-1]$. For student entrepreneurs, we look at people who graduate in year t and subsequently establish an AI company.

We conduct both university-level and individual-level analyses. For the university-level analysis, we test whether AI professors' departures from a university to the industry affect the number of AI startups established by students who graduated from this university. We look at two time windows $[t-3, t-1]$ and $[t-6, t-4]$ for the departures, where t is the graduation year of the student who establishes an AI startup after graduation. The reasoning behind these time windows is they allow us to separate the effects between those professors who have more opportunity to interact with students who graduate in year t and those with less opportunity. If a professor departs 4 to 6 years prior to student's graduation year, this professor has probably no interaction with the student.[22] The OLS specification that we use is as follows[23]:

$$
\begin{aligned}
ln(1+\text{AI Entrepreneur}_{jt}) = \alpha_t + \theta_j + \beta_1 \text{Untenured Leave}_{j,[t-3,t-1]} + \beta_2 \text{Untenured Leave}_{j,[t-6,t-4]} \\
+ \gamma_1 \text{Tenured Leave}_{j,[t-3,t-1]} + \gamma_2 \text{Tenured Leave}_{j,[t-6,t-4]} + \phi \mathbf{X_{jt}} + \varepsilon_{jt}, \qquad (1)
\end{aligned}
$$

, where α_t are the year fixed effects, θ_j are university fixed effects, $AI\ Entrepreneur_{jt}$ is defined as the number of graduates in university j in year t who start AI startups after they graduate, and other regressors are defined in Table 1. We look at the effects of tenured professors' departures and untenured departures separately because of the potential differences in their impact on students. In addition, untenured professors could be leaving academia because they were denied tenure. Therefore, departures by tenured professors are likely to have a larger effect on students.

Because of the lag between graduation and startup incorporation (the average is about 2 years), for our measure of entrepreneurs, $AI\ Entrepreneur_{jt}$, 2018 graduates have mechanically fewer AI entrepreneurs than do the 2010 graduates. We control for it by adding time fixed effects. In addition, we add university fixed effects to control for the fact that some universities produce more AI entrepreneurs because of their location near areas like Silicon Valley or other factors.

For the individual-level analysis, we consider all graduates with STEM degrees as potential future AI entrepreneurs. Specifically, we use the following Logit model:

$$
Pr(\text{AI Founder}_{ijt} = 1 | \mathbf{Z_{ijt}}) = \frac{exp(\mathbf{Z_{ijt}}\beta)}{1 + exp(\mathbf{Z_{ijt}}\beta)}, \qquad (2)
$$

where $AI\ Founder_{ijt}$ is a dummy variable that is equal to one if STEM student i graduates from university j in year t who establishes an AI startup after graduation and equal to zero if that student works for other companies or becomes an founder of non-AI startups. $\mathbf{Z_{ijt}}$ includes the exact same independent variables as in equation (1).

[22] We use a window instead of putting a specific year because it is difficult to determine precisely the year when a professor actually stopped perform its teaching and supervisory duties at the university. Professor can take a leave of absence before they officially resign.

[23] Because the dependent variable, $A.I.\ Entrepreneur_{jt}$, is count data, we also use a Poisson model with the same regressors.

In addition, to test the effects of faculty departures on students' ability to attract startup funding, we use the following OLS model:

$$\text{Funding Amount}_{ijkt\tau} = \alpha_\tau + \theta_j + \gamma_1 \text{Tenured Leave}_{j,[t-1,t-3]} + \gamma_2 \text{Tenured Leave}_{j,[t-4,t-6]} + \phi \mathbf{X_{ijkt\tau}} + \varepsilon_{ijkt\tau}. \quad (3)$$

The dependent variable, Funding Amount$_{ijkt\tau}$, is the total funding amount from a financing round in year τ for startup k founded (co-founded) by entrepreneur i who graduated from university j in year t. α_τ is the financing year fixed effect and θ_j is the university fixed effect. Control variables include the entrepreneurs' degrees and prior exit (acquisition or IPO) experience, the number of founders, and firm age and the number of investors at each financing round.

3.3 Extensive Margin

To conduct a regression analysis, we select North American universities that produced at least one AI entrepreneur who received his/her highest degree from 2010 to 2018. This selection criterion yields 69 universities, 59 of which are American and 10 of which are Canadian universities. Table 3 presents summary statistics for these 69 universities from 2010 to 2018. All the variable definitions are presented in Table 1.

3.3.1 University-Level Analysis

Table 4 provides a university-level analysis of the effects of AI professors' departures for an industry job on universities' alumni entrepreneurship. The sample includes the students who received their highest degree during the 2010-2018 period from the 69 universities.

Both the OLS regression in columns (1) and the Poisson regressions in columns (3) show that tenured professor departures in $[t-6, t-4]$ have a statistically significant (at the 5% significance level) negative effect on the number of graduates in year t who later become entrepreneurs. Untenured faculty leaving for an industry job has no effect. In terms of economic significance, the Poisson regression specified in column (3) implies that a one standard deviation increase in

Tenured Leave$_{[t-6,t-4]}$ results in about a 13%[24] decrease in the number of AI entrepreneurs who establish AI startups after graduation. Given the exponential growth of faculty departures, the effect could be larger in the future. In addition, columns (2) and (4) of Table 4 show that the negative effects are concentrated in tenured AI professors who accepted a full-time industry job.

Table 5 examines whether the effects in Table 4 are heterogeneous with respect to the CS department's ranking. As shown in columns (1) through (3), the effects are much stronger for the Top 10 CS departments, as ranked by CSRanking.org based on the number of publications and adjusted for faculty size.

3.3.2 Individual-Level Analysis

Table 6 presents an individual-level analysis that tests the effects of past AI professors' departures for industry jobs on the probability that a student will become an AI entrepreneur. The sample includes all the students whose highest degree is in STEM and who received their degree during the 2010-2018 period and from one of the 69 universities that produced at least one AI entrepreneur during that period. All specifications are based on a Logit model.

The coefficient on Tenured Leave$_{[t-4,t-6]}$ is statistically significant (at the 1% significance level) in column (1).[25] Moreover, Table 6 shows the heterogeneous effects with respect to the startup's location and whether they hold a PhD degree.

Columns (2) and (3) examine whether professors' departures have a bigger impact on entrepreneurs who hold a PhD degree.[26] The coefficient on *PhD* is positive and statistically significant at the 1% significance level, which is consistent with Table 2, which shows that a higher portion of AI entrepreneurs have a PhD compared to non-AI entrepreneurs. More importantly, the coefficients on the interaction terms, PhD$\times$Tenured Leave$_{[t-6,t-4]}$ and PhD$\times$Tenured Complete Leave$_{[t-6,t-4]}$

[24] As shown in Table 3, the sample standard deviation of Tenured Leave$_{[t-6,t-4]}$ is 0.05 and the coefficient on Tenured Leave$_{[t-6,t-4]}$ is -2.75. Therefore, the 13% decrease is calculated as $exp(-2.75 \times 0.05) - 1 = -0.13$.

[25] Specification (1) in Table 6 implies that a one standard deviation increase in the tenured AI professors' departures during time window $[t-6, t-4]$ indicates a 21% decrease in odds ratio. And it is calculated as $exp(0.05 \times -4.66) - 1 = -0.21$.

[26] Using the expulsion of mathematics professors in Nazi Germany as an exogenous source of variation, Waldinger (2010) shows that faculty quality has a significant positive effect on PhD students' both short-term and long-term performance.

, are negative and statistically significant at 10% and 5% significance level, respectively, indicating that tenured professor departures have a bigger impact on PhD students.

Columns (4) and (5) examine whether faculty departures also affect the location of new AI startups. Specifically, we test whether AI faculty departures decrease the probability that entrepreneurs start AI firms in the same city where the university from which they graduated is located. The dependent variable in columns (4) and (5), Local AI Founder, is a dummy variable that is equal to one if an AI entrepreneur starts an AI startup in the same city where the university from which he/she received his/her highest degree is located. Conditional on the AI founders, we do not find any evidence that tenured AI faculty departures result in fewer local AI founders.

3.3.3 Deep Learning

Recent advancements in deep learning algorithms is a major factor in the renewed interest in AI. Figure 6 shows the exponential growth in Google search index for the term "deep learning" and in the total number of Google citations for the three most influential deep-learning papers published before 2010 by the three 2018 Turing Prize winners.

AI, and in particular the deep learning, is claimed to be the next General Purpose Technology (GPT) (see Aghion, Jones, and Jones 2017, Brynjolfsson, Rock, and Syverson 2017, Trajtenberg 2018). In addition to GPT, deep learning could be the Invention of the Method of Invention (IMI), a term coined by Griliches (1957) in his seminal work on hybrid corn. Cockburn, Henderson, and Stern (2018) write "If it [deep learning] is also a general purpose IMI, we would expect it to have an even larger impact on economy-wide innovation, growth, and productivity as dynamics play out—and to trigger even more severe short run disruptions of labor markets and the internal structure of organizations." They continue, "It is possible that deep learning will change the nature of scientific and technical advance itself."[27]

Given the importance of GPT technologies for the economy (David 1989; Autor, Katz, and

[27] See also Gil et al. (2014) who write "The challenge presented by advances in AI is that they appear to be research tools that not only have the potential to change the method of innovation itself but also have implications across an extraordinarily wide range of fields."

Krueger 1998; Bresnahan and Trajtenberg 1995; Bresnahan, Brynjolfsson, and Hitt 2002; Rosenberg and Trajtenberg 2004), in this subsection, we look specifically at AI startups in the area of deep learning. There are 106 startups in our sample that have a keyword "deep learning" in their description. Indeed, these startups operate in very different fields (cyber security, retail, breast cancer early detection, solutions for the oil and gas industry, augmented reality, sleep therapy, supply chain planning, and more), consistent with the possibility that deep learning is a general purpose technology that can be applied across many industries.

Table 7 shows whether entrepreneurs who work in the field of deep learning are affected more by AI faculty departures. Conditional on AI entrepreneurs, the result in column (2) of Table 7 shows that the coefficient on Tenured Complete Leave$_{[t-4,t-6]}$ is negative and is statistically significant (at 5% significance level). This finding implies that the negative effect, due to tenured professes who accepted a full-time industry job, is stronger for deep learning entrepreneurs than that for the sample of all AI entrepreneurs that appears in Table 6. The stronger negative effect of tenured faculty departures on deep learning startups could indicate that the knowledge transfer is more important in this subfield of AI.

Moreover, in Table 7, we also examine whether AI faculty who join large, public tech firms or who establish their own startups have a differential effect on deep learning entrepreneurs, compared to other types of AI entrepreneurs. The results from the Logit regressions in columns (3) and (4) do not exhibit such a differential effect.

3.3.4 Endogeneity and the Instrumental Variable Approach

As discussed earlier, location specific unobservable factors could potentially explain the effects we present so far. To address this endogeneity issue, we need some exogenous variation that can predict professors' departures but that have no correlation with location-specific factors.

We use the average number of citations as an instrument variable to establish a causal relationship. A high number of citations is likely to attract more industry attention and thus is more likely to generate an offer for the professor to leave academia. As for the exclusion condition, our instrument needs to affect the number of AI entrepreneurs only via AI professors' departures. Because the citations are from researchers around the world and are mainly based on past published papers, it is unlikely that our instrumental variable is correlated with unobservable local factors that affect the number of future alumni AI entrepreneurs.

Average AI citations could also be a proxy for the quality of a university's AI faculty quality; universities with high-quality AI faculty are likely to produce more AI entrepreneurs. However, our results indicate the opposite. In addition, given the persistence of the university's faculty quality, AI faculty quality is largely controlled by the university fixed effect. We also control for CS department ranking, defined in Table 1.

We use the following 2SLS model

$$\text{High Tenured Leave}_{j,[t-4,t-6]} = \alpha_t + \theta_j + \beta_1 \text{Average Citation}_{j,[t-4,t-6]} + \gamma_1 \mathbf{X}_{j,[t-4,t-6]} + \varepsilon_{jt} \tag{4}$$

$$ln(1 + \text{AI Entrepreneur}_{jt}) = \alpha_t + \theta_j + \beta_2 \text{High Tenured} \widehat{\text{Leave}}_{j,[t-4,t-6]} + \gamma_2 \mathbf{X}_{j,[t-4,t-6]} + \varepsilon_{jt}. \tag{5}$$

To improve the predictive power of the first stage, instead of using the continuous variable, $Tenured\ Leave_{[t-4,t-6]}$, we construct a dummy variable, $High\ Tenured\ Leave_{[t-4,t-6]}$, that is equal to one if a university experiences above-median departures in a given year (i.e., $Tenured\ Leave_{[t-4,t-6]}$ is above the median level in year t). It is easier to predict whether a university will experience more faculty departures for industry jobs relative to other universities than to predict what percentage of AI faculty members leave for the industry based on the university's average number of citations.

Table 8 presents the 2SLS results with the average number of citations for AI professors as the instrumental variable. Consistent with the results from the OLS regression in column (1), the second-stage results from column 2 of Panel A show that the coefficient on the fitted value of High Tenured Leave$_{[t-4,t-6]}$ obtained from the first stage is negative and statistically significant at 1%. Moreover, the economic magnitude from the 2SLS regression is much larger than that from the OLS model in column (1). Since AI faculty from top schools are more likely to have high citations and get poached by firms from industry, the variation of fitted value of High Tenured Leave$_{[t-4,t-6]}$ obtained from the first stage mainly comes from top schools. As a result, the larger magnitude from the 2SLS regression is consistent with our results from Table 5 that the negative effects due to AI faculty departures are stronger for top 10 CS departments.

Column (3) in Panel A of Table 8 shows the first-stage results with a R^2 of 0.48 and a Kleibergen-Paap F Statistic of 9.01.[28] The results show that universities with AI faculty who have a high number of citations tend to have an above-median fraction of AI professors leaving for an industry job. The first-stage results are consistent with Zucker, Darby, and Torero (2002) who show that faculty quality is a major determinant of professors leaving for an industry job.

3.3.5 Placebo Tests

In addition to using an instrumental instrumental variable approach to establish the causal relationship, we also conduct a placebo test to address the concern that universities' unobservable location-specific factors may confound our results.

The test only focuses on the entrepreneurs who found AI startups in a city where they did not attend an university. If our results were driven, for example, by the closure of a local VC firm, this shock to the local startup financing environment would hinder startup activities overall, regardless of whether or not entrepreneurs are alumni of local universities.

Table 14 provides a city-level analysis with the dependent variable being the number of entrepreneurs who found AI startups in city j during year t but are who not alumni of city j's universities. For independent variables, we aggregate the university-level measures in previous tests by taking the average for each city and year. Instead of a negative correlation between faculty departures and non-alumni entrepreneurs' local startup activities because both are driven by negative local shocks, Table 14 presents a positive correlation. This positive correlation makes it implausible that negative local shocks explain why AI faculty departures reduce the number of AI startups founded by alumni.

[28]Given that it is less than the conventional threshold, 10, for weak instrument (Stock and Yogo 2002), we employ Anderson-Rubin (AR) test to draw a weak-instrument robust inference. In just-identified case with single endogenous regressor, Moreira (2009) shows that AR test is optimal because it is uniformly most powerful unbiased estimator. With 95% confidence level, the confidence set for the coefficient on $\widehat{High\,Tenured\,Leave}_{[t-4,t-6]}$ is $[-\infty, -0.203]$. Weak-instrument robust inference indicates that the coefficient is negative and statistically significant at 5%.

3.4 Intensive Margin (Early-Stage Entrepreneurial Financing)

Next we test whether AI faculty departures for an industry job have a negative impact on students' ability to attract funding. As shown in Panel B of Table 2, as of year 2018, 85% of the AI startups in our sample are still in the early stage (i.e., no later than series A round). Therefore, our focus is on the first and series A rounds. Table 2 also shows that compared to other IT startups, AI startups raised \$1.01 million more in first round and \$2.9 million more in series-A round.

Table 9 shows the effect of AI faculty departures on AI startups' first-round funding. The OLS results in columns (1) and (2) show that the coefficients on both departure measures, $Tenured\ Leave_{[t-6,t-4]}$ and $High\ Tenured\ Leave_{[t-6,t-4]}$, are negative and statistically significant at the 1% level. This result implies that AI startups with founders who are negatively affected by AI faculty departures, attract less funding in the first round. A one standard deviation increase in $Tenured\ Leave_{[t-6,t-4]}$ results in about a \$0.6 million decrease in first-round funding.[29] The sample average for the first-round funding for AI startups is \$2.7 million. As a result, a one standard deviation increase in the $Tenured\ Leave_{[t-6,t-4]}$ leads to about a 22% decrease in first-round funding relative to the sample average.

Columns (3) and (4) show the 2SLS results with the average number of citations for AI professors as the instrumental variable, the same instrumental variable used in the previous analysis. The coefficient on the fitted value of $High\ Tenured\ Leave_{[t-4,t-6]}$ is negative and statistically significant at the 1% level. Because the coefficient on faculty departure during the time window $[t-3, t-1]$ ($Tenured\ Leave_{[t-3,t-1]}$) is not statistically significant in the OLS regressions, we do not include it in the 2SLS. In addition, the Kleibergen-Paap F statistic from the first stage is 134, which is greater than the threshold, 10, for weak instruments (Stock and Yogo 2002), and the R^2 from the first stage is 0.75.

Table 10 shows the effect of AI faculty departures on the series-A funding round of AI startups. The OLS regressions in columns (1) and (2) show that the coefficients on both departure measures,

[29] The standard deviation of $Tenured\ Leave_{[t-6,t-4]}$ is 0.05. The coefficient on $Tenured\ Leave_{[t-6,t-4]}$ in column (1) of Table 9 is -12.1.

Tenured Leave$_{[t-6,t-4]}$ and *High Tenured Leave*$_{[t-6,t-4]}$, are negative and statistically significant at the 5% level, consistent with the findings from the first-round funding regressions. In terms of economic significance, a one standard deviation increase in the *Tenured Leave*$_{[t-6,t-4]}$ results in about a \$3.15 million decrease in series-A round funding.[30] The sample average for the series-A round funding for AI startups is \$11.3 million. As a result, a one standard deviation increase in the *Tenured Leave*$_{[t-6,t-4]}$ leads to about a 28% decrease in series-A round funding, relative to the sample average.

Columns (3) and column (4) in Table 10 report the first-stage and the second-stage results of 2SLS respectively. The coefficient on the fitted value of *High Tenured Leave*$_{[t-4,t-6]}$ is negative and statistically significant at the 1% level.. In addition, from the first stage regression, the R^2 is 0.78 and the Kleibergen-Paap F statistic is 21.

Table 11 shows the effect of AI faculty departures on the funding growth from the first round to the second round. The OLS regressions in columns (1) and (2) show that the coefficients on both departure measures, *Tenured Leave*$_{[t-6,t-4]}$ and *High Tenured Leave*$_{[t-6,t-4]}$, are negative and statistically significant at the 1% level. In terms of economic significance, a one standard deviation increase in the *Tenured Leave*$_{[t-6,t-4]}$ could decrease the funding growth rate of a representative AI startup in our sample from 530% to 415%.[31]

Columns (3) and column (4) in Table 11 report the first-stage and the second-stage results of 2SLS respectively. The coefficient on the fitted value of *High Tenured Leave*$_{[t-4,t-6]}$ is negative and statistically significant at the 1% level. In addition, from the first stage regression, the R^2 is 0.78 and the Kleibergen-Paap F statistic is 19.8.

[30] The standard deviation of *Tenured Leave*$_{[t-6,t-4]}$ is 0.05. The coefficient on *Tenured Leave*$_{[t-6,t-4]}$ in column (1) of Table 10 is -63.1.

[31] The sample average for the funding growth rate from the first to the second round is about 530%, the standard deviation of *Tenured Leave*$_{[t-6,t-4]}$ is 0.05, and the coefficient on *Tenured Leave*$_{[t-6,t-4]}$ in column (1) of Table 11 is -23.1.

3.5 Can AI professors be replaced?

In this subsection, we examine whether new AI professors, who join the university during the the time window $[t-3,t-1]$, can remedy the negative effects due to the AI faculty who leave for an industry job during the time window $[t-6,t-4]$. Moreover, we investigate whether the new tenured/untenured professors have a heterogeneous effect. We also condition on the ranking of the department that tenured faculty come from (see variable definition in Table 1).

In columns (1) and (2) of Table 12, we examine whether new AI tenured/untenured professors, who come to the universities that previously experienced AI faculty departures, can remedy the negative effects due to the tenured faculty departures. The coefficients on both interaction terms, Tenured Leave$_{[t-6,t-4]}$ $\times$ Untenured Move In$_{[t-3,t-1]}$ and Tenured Leave$_{[t-6,t-4]}$ $\times$ Tenured Move In$_{[t-3,t-1]}$ are statistically insignificant, suggesting that new professors, regardless of tenured or untenured, are unable to offset the negative effects on student entrepreneurship.

In columns (3) and (4) of Table 12, we examine whether professors who come from the higher ranked universities have a heterogeneous impact on students' entrepreneurship than those who come from lower ranked institutions. In column (3), the coefficient on the interaction term between Tenured Leave$_{[t-6,t-4]}$ and Move In From Low$_{[t-3,t-1]}$ (i.e., the number of professors who come from lower ranked universities during $[t-3,t-1]$ scaled by the AI faculty size) is negative (significant at the 1% level), suggesting that the negative effects is worsened by faculty who come from lower ranked universities. Furthermore, even for professors who come from higher ranked universities, the negative effect is not offset, as suggested by the results from column (4).

The findings from columns (1) through (4) in Table 12 suggest that AI professors who leave for industries are probably the top researchers in the field of AI and are hard to replace them with someone of similar quality, especially during the times when all departments are experiencing some level of brain drain. As a result, students continue to be negatively affected by AI faculty who joined industry four to six years prior to their graduation even if new AI faculty come in to replace them.

Besides the 221 departures from academia to the industry, there are also 160 departures to a different North American university.[32] In columns (5) and (6), we study whether the effect of the AI faculty departures to other universities on AI startups is the same as the effect of faculty departures to the industry. Unlike the findings for AI faculty who accepted an industry job, the results in column (5) of Table 12 show that tenured or tenure-track professors who move to other North American universities do not have negative effects on AI startups. This could be due to several reasons. First, AI faculty who accept industry jobs might be different from those who choose to stay in academia in terms of the quality, as our results shown in columns (1) through (4) that AI faculty who accepted industry jobs are probably top researchers and are hard to be replaced. Second, professors who move to another university can still advise their PhD students from their old university. In addition, unlike leaving for industry, faculty leaving for another university is sometimes expected and planned ahead, which could reduce the negative effect if there is any.

In column (6), we separately examine faculty who moved to other universities that are ranked higher and those who moved to other universities of equal or lower rank. Interestingly, faculty who moved to a lower ranked university show a positive effect on AI startups by university graduates of their old universities. The positive effect exists for departures that took place mainly 4-6 years prior to the students' graduation. This positive effect can come from a reduced exposure to a low quality teaching, or from getting access to better professors who replace the ones who leave.

3.6 An Aggregate Effect of AI Faculty Departures

In this subsection, we test whether AI faculty departures at a given university induce would-be AI entrepreneurs to pursue their studies at other universities or in different fields of IT at the same university. If a university's decline in alumni's AI startups due to AI faculty departures is offset by an increase in AI startups at other universities or an increase in startups in other fields of IT, then the findings presented so far imply only a redistribution of prospective students/entrepreneurs and the total number of high-tech startups is not affected.

We first examine whether AI faculty departures at one university is positively correlated with

[32] We extract this information from the faculty LinkedIn profiles.

the number of entrepreneurs from other fields of IT. In column (1) of Table 13, based on the OLS model, we find a negative correlation between tenured AI faculty departures during the time window $[t-6, t-4]$, whereas in column (2) Table 13, based on the Poisson model, we find a positive one but statistically insignificant. The mixed evidence, based on the different specifications, does not support the idea that students are pushed to other fields of IT due to AI faculty departures.

We then examine whether AI faculty departures at one university would induce would-be AI entrepreneurs to study AI at other universities that are either in the same geographical region or ranked similarly. Columns (3) and (4) in Table 13 examine the prospective student redistribution within the universities that have similar CS department rankings. Specifically, we divide the 69 universities in our sample into five groups, based on the variable, Rank, that is defined in Table 1. We then test whether AI faculty departures during the time window $[t-6, t-4]$ at one university can predict the sum of AI entrepreneurs who graduate in year t from other universities within the same ranking group. We do not find any evidence supporting students redistribution within the universities that have similar CS department ranking.

In columns (5) and (6), we examine students redistribution within a region. We select 36 universities in our sample based on 12 regions, the details of which are shown in Table 13. The dependent variable is the sum of AI entrepreneurs who graduated in year t from a university in the same region but not the university in question. For example, we would regress the number of AI startups by Harvard alumni on AI faculty departures at MIT. Consistent with the results from testing students redistribution within the same ranking group, the results from columns (5) and (6) do not support student redistribution within a region.

The findings in Table 13 suggest that would-be AI entrepreneurs do not respond to AI faculty departures by pursuing their AI studies at other less affected universities or pursing their studies in other fields of IT. We conclude that 221 AI faculty departures to the industry had an aggregate effect on the number of AI startups.

4 Economic Channels for the Effect of the Brain Drain on Indirect Innovations

The brain drain of AI professors into the industry can affect the number of AI startups established by students at the affected universities via several channels. Below we discuss each channel and the implications of our findings.

4.1 Economic Channels

Knowledge Transfer. AI startups require a highly specialized human capital that constitutes a high barrier to entry for many potential entrepreneurs.[33] Table 2 shows that in our sample, 26% of AI entrepreneurs hold a PhD degree, whereas it is only 10% for non-AI entrepreneurs. Moreover, 29% of AI entrepreneurs' highest degrees is a Master's degree, while 21% of non-AI entrepreneurs' highest degree is a Master's degree. The knowledge transfer channel attributes the negative effect of AI faculty departures on startups to the reduced quality and quantity of AI knowledge acquired by students. If students do not have access to the best AI professors then they are less likely to become AI entrepreneurs after graduation.

We find a strong empirical support for this channel. First, we show that the effect is the strongest for PhD students, students in the top universities, startups in the area of deep learning, departures by tenured professors, and departures by professors four to six years prior to students' graduation.[34] Second, the IV regression results show that professors with the highest levels of knowledge, proxied by the number of their citations, are more likely to leave academia. The negative effect on entrepreneurship is driven by departures that are predicted by citations, suggesting that the results comes from departures of the more knowledgable professors and not the less knowl-

[33]Medium (Stanford 2018) writes, "In a report, Paysa found that 35 percent of AI positions require a Ph.D. and 26 percent require a master's degree. Why? Because AI is a rapidly growing field and when you study at the Ph.D. level and participate in academic projects, they tend to be innovative if not bleeding edge, and that gives the student the experience they need for the work environment."

[34]Interaction with the faculty is particularly important for PhD students. The quality of knowledge to be transfered to students is probably higher for tenured professors in top universties. Deep learning requires high training and the scarcity of knowledge makes the knowledge transfer particularly important. Departures that take place prior to students' enrollement to the program reduce students' ability to acquire knowledge more than departures that happen after students enroll and take some classes from the departing professors.

edgable. In fact, we find that when the departing professors are replaced by professors from a lower ranked computer science departments, the negative effect of the departures to the industry is even stronger.

Following Professors. A professor's departure for an industry job may increase the probability that the professor's previously supervised students will join his or her current firm. When professors help students to get lucrative positions at their companies, it could increase the opportunity costs of establishing a startup.

If that was the explanation for the negative effect of faculty departures on the number of startups by students, we would expect to this negative effect especially pronounced for faculty departures that take place one to three years prior to students' graduation, rather than for departures that take place four to six years prior to graduation. Faculty who overlapped with a student at the university are more likely to hire this student post-graduation than faculty who did not interact with the student as much or who do not even meet the student. Our empirical results show that the negative effect exists for departures that take place four to six years prior to graduation and there is no effect for the more recent departures. It means that the reduction in the number of startups is unlikely to be explained by students following professors to join their companies and to forego the opportunity to establish their own startup.

School Selection. We would expect fewer students who are interested in AI enroll to an university that has experienced a lot of AI faculty departures. As a result, faculty departures could affect AI entrepreneurship by a decline in enrollment of future AI entrepreneurs, who instead enroll at other universities that are less affected by AI faculty departures.

In Table 13, we do not find any evidence that AI faculty departures cause student redistributions either within a region or within the universities of similar rank, which is inconsistent with school selection channel. Besides student redistribution tests, in Table OA2 in Online Appendix, we test whether AI faculty departures affect universities' ability to attract talented students. To measure the quality of incoming students, we use the number of recipients of the NSF Graduate Research Fellowship Program (GRFP) in the AI field as a proxy for student quality. If faculty departures negatively affect enrollment by high quality students, who later become AI entrepreneurs, we would expect to see a drop in the GRFP recipients following faculty departures. We do not find such an effect of tenure departures neither in the $[t-3,t-1]$ nor in the $[t-6,t-4]$ window on the number of the fellowship recipients in year t at a given university. Together, these findings suggest that the school selection channel is unlikely to be the main channel for the drop in the number of AI entrepreneurs following AI faculty departures to the industry.

Substitution to other fields. Departures of AI faculty could cause would-be AI entrepreneurs to switch to other fields. For example, if a student is interested in AI but majors in a different field or switches a thesis topic because of the lack of faculty to teach AI classes or supervise AI research.

In columns (1) and (2) of Table 13, we test whether AI professor departures affect the number of graduates from the same university who later establish startups in other fields of information technology. We do not find an empirical support for the substitution effect because AI faculty departures do not positively affect the number of non-AI startups in other files of information technology.

Professors' VC connections. It could be that an AI professor does not contribute any knowledge to students, but rather helps them find investors. When faculty departs for the industry, future students lose the industry connections that these professors have.

According to the connection channel, the negative effect of faculty departure should be stronger for local startups because professors are more likely to know VCs in their city. Table 6 shows that the negative effect of AI faculty departures is not driven by students who establish their startups in the same city as their universities' city. To further test the VC connection channel, Table OA1 in the Online Appendix shows that, conditional on being AI entrepreneurs, AI founders who are affected by AI faculty departures are not more likely to have co-founders who hold an MBA degree. If the founders have difficulties to get VC connections due to faculty departures, they should be more likely to partner with MBAs who can find such connections via their b-school's alumni network. We do not find a support for this explanation.

We conclude that the knowledge transfer channel is the main channel to explain the results.

4.2 Implications of the Findings

The implication of the knowledge diffusion channel is that firms who hire highly specialized AI professors do not (fully) internalize the negative effect such hires have on students' startups. Moreover, it is possible due to faculty departures students who are not entrepreneurs do not receive an important knowledge as well. As a result, companies that hire AI professors could be reducing the potential AI workforce for themselves and others. A smaller supply of AI talent further increases firms' incentives to hire AI faculty. This dangerous spiral negatively affects human capital accumulation. Given the important of human capital for innovations, it can result in a reduction of innovations both by large public firms and by startups. Eventually, the reduction in the accumulation of human capital and innovations can translate into a long-run effect on economic growth, especially given the GPT and IMI nature of the AI technology.[35]

Another implication of AI faculty poaching by firms is that it can reduce the number of PhD students who then become AI professors. These "unborn" AI professors are never able to transfer knowledge to their students. That generates a reduction in innovation by indirect students of the departing professors. For AI to live up to its potential to become the new GPT that spurs economic growth, the AI knowledge that is possessed now by a small number of AI professors should continue to diffuse until it becomes wide spread. Our results imply that this knowledge diffusion process is at risk due to the brain drain from academia. The discussion of the potential public policy intervention to restore the diffusion of the critical knowledge is beyond the scope of this paper.

Lastly, there is potentially a broader implication of our findings to the brain drain of AI talent between countries. If the returns on human capital in the area of AI are particularly high in

[35] A large number of seminal papers show both theoretically and empirically the importance of innovations (e.g., Solow 1956; Lucas 1988; Romer 1990) and human capital (e.g., Romer 1989; Murphy, Shleifer, and Vishny 1991; Barro 2001) on economic growth. Moreover, Gennaioli et al. (2012) find a large effect of entrepreneurial human capital on productivity.

developed countries, corporations in these countries would have incentives to hire AI professors from developing countries. If the best funded universities in the world are not able to retain their faculty (see Figure 3), how can institutions of higher education in developing countries compete globally for their very scarce AI talent? Without this talent, developing countries would not be able to participate in the AI revolution. A study of the AI brain drain in the international context and its implications on growth, development, and inequality is an important topic that we leave for future research.

5 Conclusion

The AI revolution has the potential to change every aspect of our lives. Whether AI can live up to high public expectations depends on the availability of highly specialized human capital in fields such as deep learning, cloud computing, and robotics. As companies leverage on Big Data and cloud computing to transition to AI-driven automation, the demand for labor skilled in AI will only continue to increase. AI professors at North American universities are being offered compensation packages by corporations that universities cannot match. We document that between 2004-2018, 221 professors at North American universities accepted an industry job. The reallocation of AI human capital from research universities to the private sector has important consequences for the entrepreneurship activity of the students in the affected universities. Following AI faculty departures, we find a negative causal effect on the quantity and quality of innovation, measured using the entrepreneurship data about 3,000 STEM alumni, 363 AI entrepreneurs, and 177 AI startups. We conclude that knowledge transfer via higher education is an important channel for the diffusion of AI-driven technological change.

There are a number of other cases when the invention had a profound effect on an existing industry (e.g., the invention of option pricing by Fischer Black, Myron Scholes, and Robert Merton) or even created a new industry (e.g., the invention of rDNA technology by Herbert Boyer and Stanley Cohen). All these inventions were followed by some brain drain from academia. It is possible that these faculty departures had a previously undocumented negative effect on the domain-specific transfer of knowledge to students and future entrepreneurs. What is special about the AI revolution that we study in this paper is its fast-growing economy-wide impact. The deep learning neural networks developed by Geoffrey Hinton, Yann LeCun, and Yoshua Bengio have applications in healthcare, finance, manufacturing, research, astrophysics, cybersecurity, entertainment, and more. The large negative impacts on innovations that we document is mostly driven by departures that took place in 2012 - 2014. With the exponential growth in the number of AI faculty departures, the actual effect on future innovation could be much larger. Moreover, with this exponential growth, the implications of our study can become relevant not only for innovation, but also for immigration, workforce automation, and ultimately economic growth.

The AI brain drain from universities affects innovation by firms, universities, and students. In this paper, we focus on the latter. In future research, it would be interesting to study the effect of AI faculty departures on the productivity of companies they join, the knowledge creation in the universities that they leave, and on the labor market outcomes of AI students in the affected universities. This analysis would give policy makers a more comprehensive picture of the net effects of the brain drain on productivity and on externalities in the labor market for AI talent.

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Figure 1

This figure shows the number of tenure-track and tenured AI professors leaving each year for an industry and the citation ratio of AI faculty who left for an industry job to all AI faculty for each year. The citation ratio is calculated using the sum of citations from faculty who left for industry (stock at the time of departure) divided by the sum of citations from all AI faculty for each year and each university; we then take the average across universities for each year.

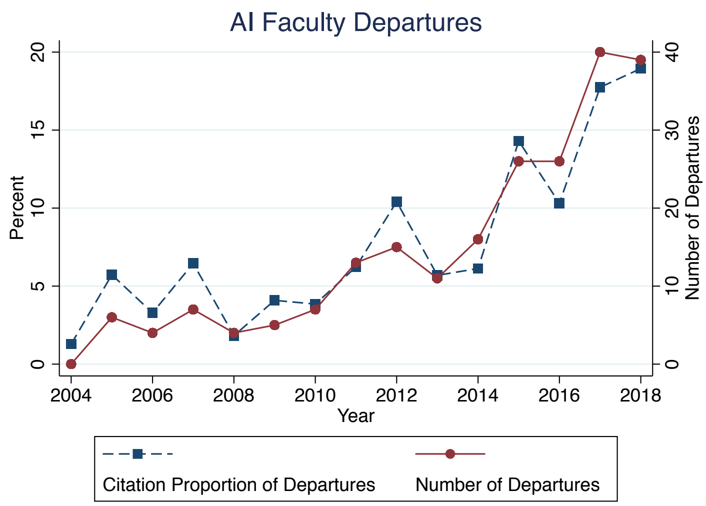

Figure 2

This graph shows the number of AI related tenure-track professors in North America leaving each year for an industry job. This graph also shows the average size of AI faculty in computer science department ranked in top 100 in North America for each year from 2004 - 2018. The ranking information is provided by CSrankings and is based on publications.

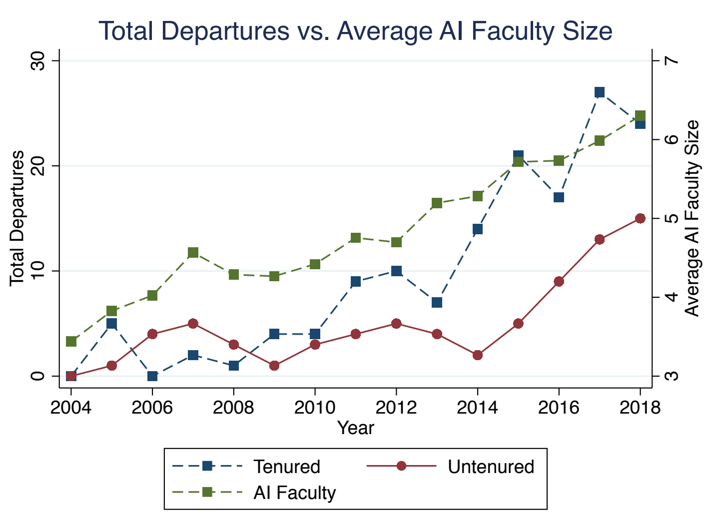

Figure 3

This figure shows North American universities with the largest losses of AI related tenure-track or tenured professors.

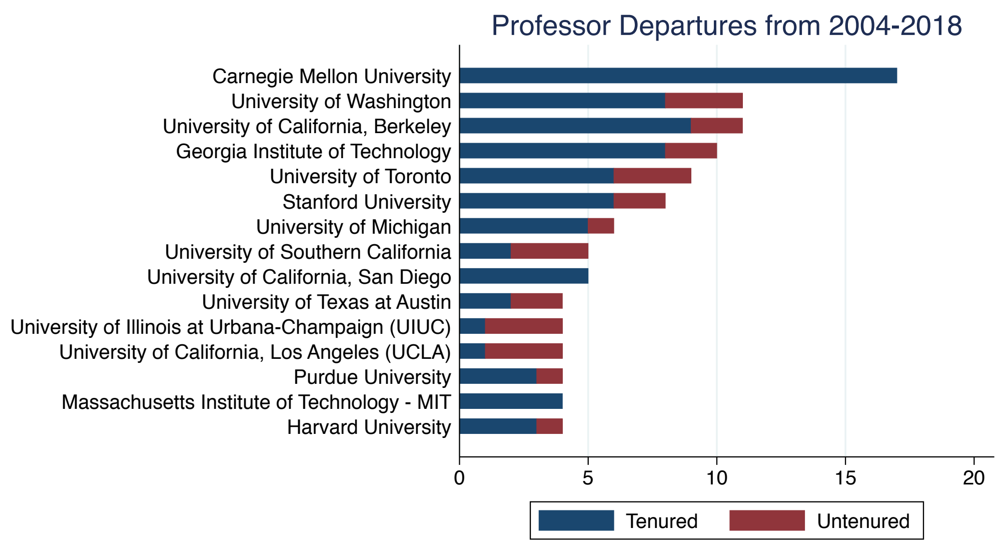

Figure 4

This graph shows the number of AI professors poached by the 19 publicly traded firms in the sample from 2004 - 2018.

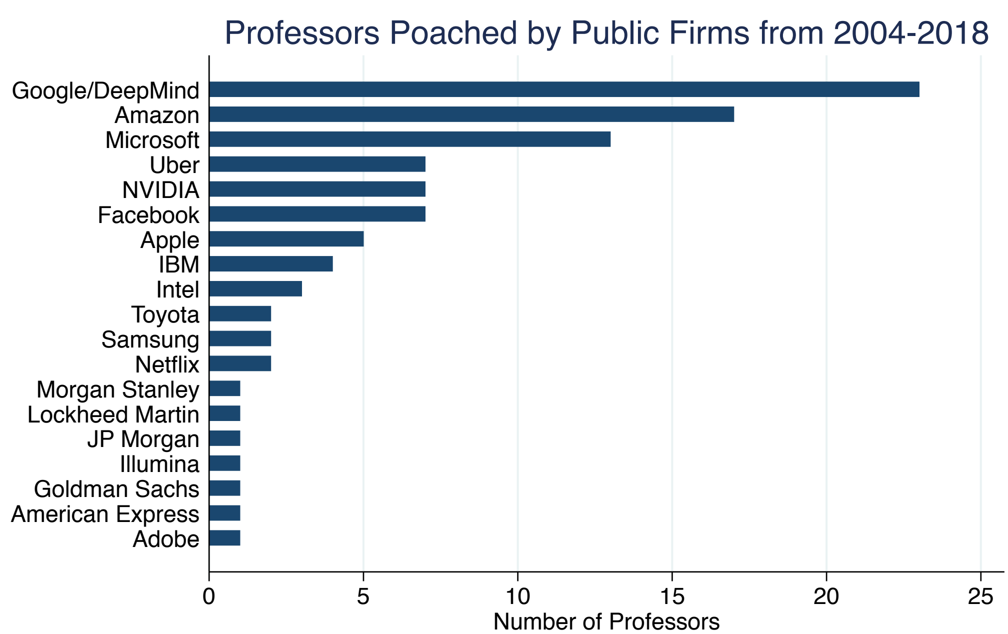

Figure 5

This graph shows North American universities that produced the most AI entrepreneurs who received their highest degrees from these universities from 2004 - 2018 and who started AI startups thereafter.

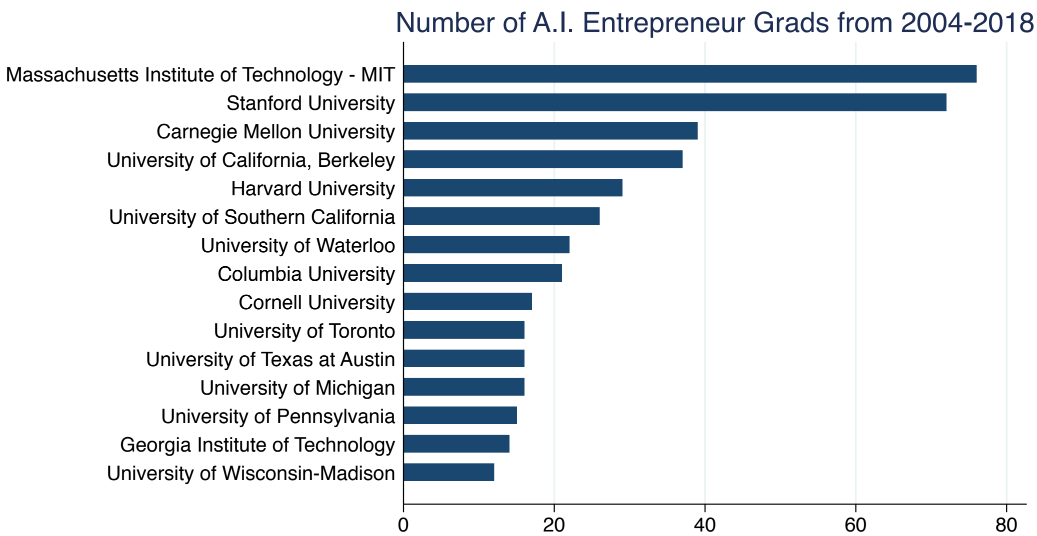

Figure 6

This graph shows the Google search index for the word "deep learning" for each year and the total number of citations of the three most influential deep-learning related papers published before 2010: LeCun et al. (1998), Hinton, Osindero, and Teh (2006), and Bengio (2009). Geoffrey Hinton, Yann LeCun, and Yoshua Bengio won the Turing Award in 2019 for their contributions to deep learning.

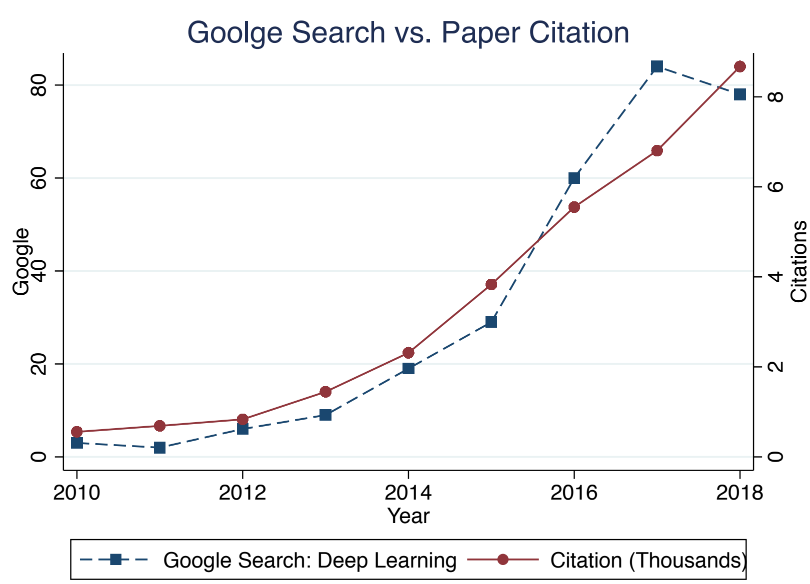

Table 1: Variable Definitions

Variable Name	Definition
AI Faculty	AI faculty size for each year and university
Untenured Leave	Number of tenure-track assistant AI professors, scaled by *AI Faculty*, at North American university i in year t accepting an industry job
Tenured Leave	Number of tenured AI professors, scaled by *AI Faculty*, at North American university i in year t accepting an industry job
Partial Leave	Number of AI professors, scaled by *AI Faculty*, accepting an industry job while keeping the university position at university i in year t
Complete Leave	Number of tenured AI professors, scaled by *AI Faculty*, accepting an industry job without keeping the university position at university i in year t
Move Out	Number of AI professors leaving North American university i in year t for another North American university, scaled by *AI Faculty*
Move In	Number of AI professors coming to North American university i in year t, scaled by *AI Faculty*
Rank	A continuous measure for a computer science department ranking based on the department's presence in the most prestigious publication venues provided by CSRanking.org
Move In From Low	Number of AI professors coming to North American university i in year t from another lower ranked North American university, based on the variable, Rank, scaled by *AI Faculty*
Move In From High	Number of AI professors coming to North American university i in year t from another North American university of equal or higher rank, based on the variable, Rank, scaled by *AI Faculty*
Untenured Leave$_{[t-3,t-1]}$	$\sum_{i=3}^{1} Untenured\ Leave_{t-i}$
Tenured Leave$_{[t-3,t-1]}$	$\sum_{i=3}^{1} Tenured\ Leave_{t-i}$
HighTenuredLeave$_{[t-6,t-4]}$	A dummy variable that is equal to one if a university in a given year is above the median level based on the variable, *Tenured Leave*$_{[t-6,t-4]}$
Average Citation$_{[t-6,t-4]}$	Average citation of AI professors in a given university during the period $[t-4,t-6]$
AI Entrepreneur$_{jt}$	Number of AI entrepreneurs who graduate in year t from university j and establish AI startups after graduation
AI Founder$_{ijt}$(Dummy)	Equal to one if student i who graduates in year t from university j and establishes an AI startups after graduation
IT Entrepreneur$_{jt}$	Number of entrepreneurs who graduate in year t from university j and establish information technology startups (excluding AI) after graduation
Single Founder	Entrepreneurs who start a new firm without co-founders
Local Founder	Entrepreneurs who start a new firm in the same city where the university from which they received their highest degree is located
PhD	Entrepreneurs who hold a PhD degree
Master	Entrepreneurs whose highest academic degree is a Master's degree
Bachelor	Entrepreneurs whose highest academic degree is a Bachelor's degree
Found Lag	Lag between graduation and establishing a startup
NSF	Number of recipients of an NSF Graduate Research Fellowship in the AI field in year t at university j

Table 2: AI vs. Non-AI (IT)

This table includes entrepreneurs who received the highest degree between 2010 and 2018 and who start firms after they receive the degree. Non-AI entrepreneurs are founders who establish information technology (IT) related startups (excluding AI) after graduation. Panel A compares the characteristics of AI entrepreneurs and Non-AI entrepreneurs. All variables in Panel A are defined in Table 1. Panel B compares the characteristics of AI startups and Non-AI startups. Early Stage is a dummy variable that is equal to one if the latest funding round is no later than series A. Average Found Lag is the average lag between graduation and the graduate founding a startup firm. Prior Exit is the percentage of founders who had prior exit experience (acquisition or IPO). PhD is the percentage of startups with at least one founder holding a PhD degree. *, **, or *** indicates that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Panel A: Entrepreneur

	N(AI)	N(IT)	Mean(AI)	Mean(IT)	Diff.	SE
Single Founder	363	985	0.14	0.22	-0.07***	0.024
Local Founder	363	985	0.17	0.19	-0.02	0.024
Bachelor	363	985	0.28	0.45	-0.17***	0.030
Master (Non-MBA)	363	985	0.29	0.21	0.08***	0.026
MBA	363	985	0.05	0.09	-0.04**	0.017
PhD	363	985	0.26	0.10	0.16***	0.021
Found Lag	363	985	2.24	1.89	0.35***	0.114
Observations	1348					

Panel B: Startup

	N(AI)	N(IT)	Mean(AI)	Mean(IT)	Diff.	SE
Early Stage Status	177	591	0.85	0.80	0.06*	0.034
Average Found Lag	177	591	2.45	1.93	0.52***	0.164
Prior Exit	177	591	0.09	0.17	-0.08**	0.031
Number of Founders	177	591	2.45	2.31	0.14	0.094
PhD	177	591	0.24	0.07	0.17***	0.025
First-Round Funding ($MM)	177	591	2.70	1.69	1.01**	0.412
Firm Age at First Round	177	591	0.85	0.82	0.04	0.085
Series A Funding ($MM)	62	174	11.33	8.42	2.90**	1.126
Firm Age at Series A	64	175	2.39	2.46	-0.07	0.206
Observations	768					

Table 3: Summary Statistics at University Level

Each observation in the following table is a university-year pair. The sample period is 2010 - 2018 and includes 69 universities that have at least one AI entrepreneur who graduated during the 2010 - 2018 period. All variables are defined in Table 1. For lagged variables, such as Tenured Leave$_{[t-4,t-6]}$, the sample period can extend to as early as 2004.

	N	Mean	Median	S.D.	Min	Max
AI Entrepreneur	621	0.588	0.00	1.19	0.00	8.00
Non-AI Entrepreneur	621	1.589	0.00	3.09	0.00	33.00
AI Faculty	621	7.816	6.00	6.97	0.00	45.00
Untenured Leave$_{[t-3,t-1]}$	621	0.012	0.00	0.04	0.00	0.27
Untenured Leave$_{[t-6,t-4]}$	621	0.017	0.00	0.08	0.00	1.00
Tenured Leave$_{[t-3,t-1]}$	621	0.026	0.00	0.07	0.00	0.50
Tenured Leave$_{[t-6,t-4]}$	621	0.012	0.00	0.05	0.00	0.50
Tenured Partial Leave$_{[t-3,t-1]}$	621	0.010	0.00	0.04	0.00	0.33
Tenured Partial Leave$_{[t-6,t-4]}$	621	0.004	0.00	0.03	0.00	0.30
Tenured Complete Leave$_{[t-3,t-1]}$	621	0.015	0.00	0.05	0.00	0.50
Tenured Complete Leave$_{[t-6,t-4]}$	621	0.008	0.00	0.04	0.00	0.50
Untenured Move In$_{[t-3,t-1]}$	621	0.018	0.00	0.05	0.00	0.50
Untenured Move In$_{[t-6,t-4]}$	621	0.014	0.00	0.05	0.00	0.50
Tenured Move In$_{[t-3,t-1]}$	621	0.013	0.00	0.05	0.00	0.53
Tenured Move In$_{[t-6,t-4]}$	621	0.007	0.00	0.03	0.00	0.50
Move In From High$_{[t-3,t-1]}$	621	0.025	0.00	0.06	0.00	0.50
Move In From High$_{[t-6,t-4]}$	621	0.017	0.00	0.06	0.00	0.50
Move in From Low$_{[t-3,t-1]}$	621	0.006	0.00	0.04	0.00	0.33
Move in From Low$_{[t-6,t-4]}$	621	0.004	0.00	0.03	0.00	0.50

Table 4: University-Level Analysis

This table shows the effects of AI professors' departure for the industry on universities' ability to train next-generation AI entrepreneurs. The dependent variable for the OLS model in columns (1) and (2) is $ln(1 + AI\ Entrepreneur)$ where AI Entrepreneur is defined in Table 1. The dependent variable for the Poisson model in columns (3) and (4) is AI Entrepreneur. Each observation is a university-year pair and the sample period is from 2010 - 2018 and includes 69 universities that produced at least one AI entrepreneur graduate during that period. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicates that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable	ln(1+AI Entrepreneur)		AI Entrepreneur	
	OLS	OLS	Poisson	Poisson
	(1)	(2)	(3)	(4)
Untenured Leave$_{[t-3,t-1]}$	-0.800	-0.799	-1.590	-1.785
	(0.603)	(0.596)	(2.338)	(2.307)
Untenured Leave$_{[t-6,t-4]}$	-0.092	-0.090	0.890	1.019
	(0.109)	(0.109)	(0.887)	(0.974)
Tenured Leave$_{[t-3,t-1]}$	-0.591*		-1.969	
	(0.346)		(1.394)	
Tenured Leave$_{[t-6,t-4]}$	-0.871**		-2.748**	
	(0.364)		(1.208)	
Tenured Partial Leave$_{[t-3,t-1]}$		-0.517		-0.236
		(0.570)		(1.184)
Tenured Partial Leave$_{[t-6,t-4]}$		-1.288		-2.235
		(0.790)		(1.569)
Tenured Complete Leave$_{[t-3,t-1]}$		-0.688		-3.604
		(0.426)		(2.220)
Tenured Complete Leave$_{[t-6,t-4]}$		-0.766**		-3.214*
		(0.371)		(1.676)
Rank	-0.289	-0.281	-0.745	-0.713
	(0.299)	(0.302)	(0.536)	(0.519)
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
N	621	621	621	621
R^2	0.509	0.510		
Pseudo R^2			0.393	0.394

Table 5: Heterogeneous Effect of CS Department Ranking

This table shows whether the effects in Table 4 are heterogeneous with respect to CS department ranking. All specifications are OLS models with the dependent variable $ln(1+AI\ Entrepreneur)$. $Top10$ includes CS departments ranked in the top 10, $Top30$ includes CS departments ranked between the top 10 and the top 30, and $Top50$ includes CS departments ranked in the top 30 and the top 50. All other variables are defined in Table 1. The sample is identical to that of Table 4. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicates that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	ln(1+AI Entrepreneur)		
	OLS	OLS	OLS
	(1)	(2)	(3)
Untenured Leave$_{[t-3,t-1]}$	-0.877	-0.789	-0.767
	(0.587)	(0.607)	(0.590)
Untenured Leave$_{[t-6,t-4]}$	-0.091	-0.099	-0.080
	(0.108)	(0.108)	(0.109)
Tenured Leave$_{[t-3,t-1]}$	-0.640*	-0.596*	-0.596*
	(0.378)	(0.345)	(0.348)
Tenured Leave$_{[t-6,t-4]}$	-0.383	-0.977***	-0.944***
	(0.421)	(0.339)	(0.349)
Tenured Leave$_{[t-6,t-4]}\times$Top10	-1.493**		
	(0.671)		
Top10	0.247		
	(0.191)		
Tenured Leave$_{[t-6,t-4]}\times$Top30		0.728	
		(1.197)	
Top30		0.025	
		(0.088)	
Tenured Leave$_{[t-6,t-4]}\times$Top50			1.548
			(1.032)
Top50			-0.081
			(0.053)
Rank	-0.344	-0.304	-0.308
	(0.281)	(0.315)	(0.296)
Year FE	Yes	Yes	Yes
University FE	Yes	Yes	Yes
N	621	621	621
R^2	0.515	0.510	0.512

Table 6: Individual-Level Analysis

This table shows whether the negative effect shown from the university-level analysis is heterogeneous with respect to the location of the startups and whether the highest degree is PhD. In columns (1) through (3), each observation is a STEM student who graduated from the 69 universities specified in Table 3 during the 2010 - 2018 period, and dependent variable, *AI Founder*, is defined in Table 1. In columns (4) and (5), each observation is an AI entrepreneur, defined in Table 1, who graduated during the 2010 - 2018 period, and dependent variable, *Local AI Founder*, is a dummy variable that is equal to one if an AI entrepreneur starts an AI startup in the same city where the university from which he/she received his/her highest degree is located. For all specifications, robust standard errors are clustered at the city level and reported in parentheses. *, **, or *** indicates that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable	AI Founder			Local AI Founder	
	Logit	Logit	Logit	Logit	Logit
	(1)	(2)	(3)	(4)	(5)
Untenured Leave$_{[t-1,t-3]}$	-1.850	-2.410	-2.463	7.195	7.690
	(3.175)	(3.055)	(2.982)	(7.833)	(7.450)
Untenured Leave$_{[t-4,t-6]}$	-1.585	-1.422	-1.410	-9.320*	-6.518
	(1.409)	(1.404)	(1.396)	(5.525)	(4.810)
Tenured Leave$_{[t-3,t-1]}$	-0.430	-0.792		-1.077	
	(2.074)	(1.944)		(2.761)	
Tenured Leave$_{[t-6,t-4]}$	-4.660***	-3.312***		-9.121	
	(1.175)	(1.171)		(7.143)	
Tenured Leave$_{[t-6,t-4]}\times$PhD		-13.013*			
		(7.480)			
Tenured Complete Leave$_{[t-3,t-1]}$			-1.945		-4.657
			(3.177)		(3.259)
Tenured Complete Leave$_{[t-6,t-4]}$			-3.999***		-3.103
			(1.215)		(10.173)
Tenured Complete Leave$_{[t-6,t-4]}\times$PhD			-24.014**		
			(10.211)		
PhD		1.142***	1.065***		
		(0.197)	(0.189)		
Rank	-0.891	-0.731	-0.540	0.077	0.312
	(0.594)	(0.551)	(0.563)	(1.774)	(1.744)
Year FE	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes
N	2,739	2,739	2,739	205	205
Pseudo R^2	0.019	0.042	0.039	0.086	0.079

Table 7: Deep Learning

This table tests whether deep learning entrepreneurs are affected more by AI faculty's departure. The dependent variable, Deep Learning Founder, is a dummy variable that is equal to one if an AI entrepreneur starts a startup that specializes in deep learning. The sample includes AI entrepreneurs specified in Table 2. The sample size is reduced due to university fixed effect. Large Tech$_{[t-3,t-1]}$ is the number of AI faculty who accepted jobs from publicly traded tech companies during the window $[t-3,t-1]$ scaled by AI faculty size. Large Tech$_{[t-3,t-1]}$ plus Non-Large Tech$_{[t-3,t-1]}$ is equal to total departures for industry at a given university during $[t-3,t-1]$. Founder Leave$_{[t-3,t-1]}$ is the number of AI faculty who started their own firms during the window $[t-3,t-1]$ scaled by AI faculty size. Founder Leave$_{[t-3,t-1]}$ plus Non-founder Leave$_{[t-3,t-1]}$ is equal to total departures for industry at a given university during $[t-3,t-1]$. Other variables are defined in Table 1. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicates that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	Dependent Variable: Deep Learning Founder			
	Logit	Logit	Logit	Logit
	(1)	(2)	(3)	(4)
Untenured Leave$_{[t-1,t-3]}$	3.058	2.315		
	(8.390)	(8.294)		
Untenured Leave$_{[t-4,t-6]}$	2.080	2.212		
	(7.873)	(7.817)		
Tenured Leave$_{[t-3,t-1]}$	-0.298			
	(4.346)			
Tenured Leave$_{[t-6,t-4]}$	-7.299			
	(5.023)			
Tenured Complete Leave$_{[t-3,t-1]}$		-4.961		
		(6.905)		
Tenured Complete Leave$_{[t-6,t-4]}$		-13.355**		
		(5.229)		
Non-Large Tech$_{[t-3,t-1]}$			2.905	
			(2.788)	
Non-Large Tech$_{[t-6,t-4]}$			-4.246	
			(5.157)	
Large Tech$_{[t-3,t-1]}$			-6.179	
			(8.602)	
Large Tech$_{[t-6,t-4]}$			-6.002	
			(5.597)	
Founder Leave$_{[t-3,t-1]}$				5.779
				(3.758)
Founder Leave$_{[t-6,t-4]}$				-1.430
				(6.871)
Non-founder Leave$_{[t-3,t-1]}$				-2.832
				(4.245)
Non-founder Leave$_{[t-6,t-4]}$				-7.367
				(5.759)
Rank	-0.002	0.428	-0.029	-0.080
	(1.794)	(1.878)	(1.761)	(1.865)
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
N	303	303	303	303
R^2	0.054	0.057	0.051	0.053

Table 8: 2SLS

This table shows the 2SLS results with the average number of citations for AI professors as the instrument variable. The endogenous variable, $High\,Tenured\,Leave_{[t-4,t-6]}$, is a dummy variable that is equal to one if a university experiences above-median departures (i.e., $Tenured\,Leave_{[t-6,t-4]}$ above median level in year t). The instrumental variable, $Average\,Citation_{[t-6,t-4]}$, is the average number of citations for AI professors in a given university during period $[t-6, t-4]$. All other variables are defined in Table 1. The Kleibergen-Paap F Statistic for the first stage is 9.01. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable	ln(1+AI Entrepreneur)		High Tenured Leave$_{[t-6,t-4]}$
	OLS	2SLS	First Stage
	(1)	(2)	(3)
High Tenured Leave$_{[t-6,t-4]}$	-0.183**		
	(0.085)		
High Tenured $\widehat{\text{Leave}}_{[t-6,t-4]}$		-0.823***	
		(0.309)	
Average Citation$_{[t-6,t-4]}$			0.001***
			(0.000)
Rank	-0.280	-0.099	0.219
	(0.304)	(0.321)	(0.150)
Year FE	Yes	Yes	Yes
University FE	Yes	No	Yes
N	621	621	621
R^2	0.506	0.433	0.479

Table 9: The Impact on Entrepreneurial Financing (First Round)

This table tests whether the faculty departures affect the entrepreneurial financing of startups by university graduates. The dependent variable is the total funding amount ($MM) at the first round. Each observation is a founder-startup pair and the sample includes AI entrepreneurs who received their highest degree between 2010 and 2018 and who start firms after they receive the degree. This table shows the results of both OLS and 2SLS with the average number of citations for AI professors at a given university as the instrumental variable. The endogenous variable, $High\,Tenured\,Leave_{[t-4,t-6]}$, is a dummy variable that is equal to one if a university experiences above-median departures (i.e., $Tenured\,Leave_{[t-6,t-4]}$ above median level in year t). The instrumental variable, $Average\,Citation_{[t-6,t-4]}$, is the average number of citations for AI professors in a given university during period $[t-6,t-4]$. Prior Exit is a dummy variable that is equal to one if the founder had prior exit experience (acquisition or IPO). Founding location fixed effect is at the startup state level. The Kleibergen-Paap F Statistic for the first stage is 134. For all specifications, robust standard errors are clustered at the startup state level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	Dependent Variable: Funding($MM)			High Tenured Leave$_{[t-6,t-4]}$
	OLS	OLS	2SLS	First Stage
	(1)	(2)	(3)	(4)
Tenured Leave$_{[t-6,t-4]}$	-12.120***			
	(2.057)			
High Tenured Leave$_{[t-6,t-4]}$		-1.258***		
		(0.412)		
$\widehat{\text{High Tenured Leave}}_{[t-6,t-4]}$			-2.871***	
			(0.977)	
Average Citation$_{[t-6,t-4]}$				0.001***
				(0.000)
Rank	-7.067***	-6.618***	-4.662**	0.596***
	(1.797)	(1.762)	(2.131)	(0.081)
Number of Founders	1.403	1.456	1.619**	0.105
	(0.918)	(0.903)	(0.662)	(0.090)
Prior Exit	0.105	0.040	-0.039	-0.050
	(1.067)	(1.030)	(0.790)	(0.040)
Firm Age at Financing	1.299***	1.304**	1.261***	0.001
	(0.449)	(0.465)	(0.356)	(0.015)
Investor Count	0.248*	0.252*	0.267***	0.013***
	(0.128)	(0.124)	(0.097)	(0.004)
Financing Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Founding Location FE	Yes	Yes	Yes	Yes
N	199	199	199	199
R^2	0.426	0.424	0.419	0.749

Table 10: The Impact on Entrepreneurial Financing (Series A)

This table tests whether the faculty departures affect entrepreneurial financing of startups by university graduates. The dependent variable is the total funding amount ($MM) at the series A round. Each observation is a founder-startup pair and the sample includes AI entrepreneurs who receive their highest degree between 2010 and 2018 and who start firms after they receive the degree. This table shows the results of both OLS and 2SLS with the average number of citations for AI professors as the instrumental variable. The endogenous variable, $High\ Tenured\ Leave_{[t-4,t-6]}$, is a dummy variable that is equal to one if a university experiences above-median departures (i.e., $Tenured\ Leave_{[t-6,t-4]}$ above median level in year t). The instrumental variable, $Average\ Citation_{[t-6,t-4]}$, is the average number of citations for AI professors in a given university during period $[t-6, t-4]$. Prior Exit is a dummy variable that is equal to one if the founder had prior exit experience (acquisition or IPO). Founding location fixed effect is at the startup state level. The Kleibergen-Paap F Statistic for the first stage is 21. For all specifications, robust standard errors are clustered at the startup state level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	Dependent Variable: Funding($MM)			High Tenured Leave$_{[t-6,t-4]}$
	OLS	OLS	2SLS	First Stage
	(1)	(2)	(3)	(4)
Tenured Leave$_{[t-6,t-4]}$	-63.086***			
	(15.075)			
High Tenured Leave$_{[t-6,t-4]}$		-8.101**		
		(3.475)		
High $\widehat{\text{Tenured Leave}}_{[t-6,t-4]}$			-4.701***	
			(1.448)	
Average Citation$_{[t-6,t-4]}$				0.001***
				(0.000)
Rank	-3.774	-2.380	-4.360	0.521***
	(10.118)	(10.231)	(5.446)	(0.107)
Number of Founders	5.002*	5.721**	5.568***	0.017
	(2.307)	(2.466)	(1.756)	(0.050)
Prior Exit	-2.294*	-2.547**	-3.193***	0.172***
	(1.075)	(0.973)	(0.785)	(0.038)
Firm Age at Financing	0.645	0.602	0.763***	-0.024*
	(0.386)	(0.489)	(0.206)	(0.011)
Investor Count	0.568***	0.579***	0.541***	0.006
	(0.177)	(0.109)	(0.121)	(0.009)
Financing Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Founding Location FE	Yes	Yes	Yes	Yes
N	113	113	113	113
R^2	0.523	0.514	0.508	0.781

Table 11: Funding Growth from First to Second Round

This table tests whether the faculty departures affect funding growth of startups by university graduates. The dependent variable is the growth of total funding from first round to second round, calculated as dividing the first-round funding amount by the second-round funding amount minus one. Each observation is a founder-startup pair and the sample includes AI entrepreneurs who receive their highest degree between 2010 and 2018 and who start firms after they receive the degree. This table shows the results of both OLS and 2SLS. with average citation of AI professors as the instrument variable. The endogenous variable, $High\ Tenured\ Leave_{[t-4,t-6]}$, is a dummy variable and is equal to one if a university experiences above-median departures (i.e., $Tenured\ Leave_{[t-6,t-4]}$ above median level in year t). The instrumental variable, $Average\ Citation_{[t-6,t-4]}$, is the average number of citations for AI professors in a given university during period $[t-6,t-4]$. Prior Exit is a dummy variable that is equal to one if the founder had prior exit experience (acquisition or IPO). Founding location fixed effect is at the startup state level. The Kleibergen-Paap F Statistic for the first stage is 19.8. For all specifications, robust standard errors are clustered at the startup state level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	Dependent Variable: Funding Growth			High Tenured Leave$_{[t-6,t-4]}$
	OLS	OLS	2SLS	First Stage
	(1)	(2)	(3)	(4)
Tenured Leave$_{[t-6,t-4]}$	-23.113***			
	(3.410)			
High Tenured Leave$_{[t-6,t-4]}$		-5.218***		
		(0.737)		
$\widehat{\text{High Tenured Leave}}_{[t-6,t-4]}$			-6.982***	
			(1.224)	
Average Citation$_{[t-6,t-4]}$				0.001***
				(0.000)
Rank	1.560	6.257	8.600**	0.736***
	(4.914)	(4.760)	(4.040)	(0.071)
Number of Founders	-3.917	-3.523	-3.340	0.055
	(3.347)	(3.576)	(2.545)	(0.101)
Prior Exit	-0.895	-0.887	-0.837	0.038
	(2.622)	(2.501)	(1.719)	(0.045)
Firm Age at Financing	-1.635**	-1.679***	-1.727***	-0.007
	(0.603)	(0.534)	(0.361)	(0.027)
Investor Count	-0.806***	-0.747***	-0.728***	0.011***
	(0.221)	(0.222)	(0.169)	(0.002)
Financing Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Founding Location FE	Yes	Yes	Yes	Yes
N	123	123	123	123
R^2	0.852	0.858	0.857	0.780

Table 12: Control for Moves Whithin Academia

This table controls for faculty moves within academia and presents evidence that substitute AI professors are unable to offset the negative effects due to tenured AI faculty's departures to industry. Tenured Leave, defined in Table 1, indicates tenured AI faculty who accepted an industry job. Move In is defined as the number of AI professors coming to North American university *i* in year t, scaled by AI faculty size. Move in From Low (High) is defined as the number of AI professors coming to North American university *i* in year *t* from another lower (higher) ranked North American university, based on the variable, Rank, scaled by AI faculty size. Move Out is defined as the number of AI professors leaving North American university *i* in year *t* for another North American university, scaled by AI faculty size. Move Up (Down) is defined as the number of AI professors leaving North American university *i* in year *t* for another North American university of higher (lower) rank, scaled by AI faculty size. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	Dependent Variable: ln(1+AI Entrepreneur)					
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)
Tenured Leave$_{[t-3,t-1]}$	-0.510 (0.350)	-0.632* (0.373)	-0.691* (0.374)	-0.589 (0.354)	-0.667* (0.369)	-0.665* (0.370)
Tenured Leave$_{[t-6,t-4]}$	-0.587* (0.337)	-0.808** (0.336)	-0.781** (0.353)	-0.656** (0.311)	-0.811** (0.365)	-0.765** (0.373)
Untenured Move In$_{[t-3,t-1]}$	-0.029 (0.326)					
Tenured Move In$_{[t-3,t-1]}$		0.492 (0.352)				
Move in From Low$_{[t-3,t-1]}$			0.956 (0.639)			
Move In From High$_{[t-3,t-1]}$				-0.050 (0.207)		
Tenured Leave$_{[t-6,t-4]}$ $\times$Untenured Move In$_{[t-3,t-1]}$	-28.183 (19.741)					
Tenured Leave$_{[t-6,t-4]}$ $\times$Tenured Move In$_{[t-3,t-1]}$		-0.250 (21.906)				
Tenured Leave$_{[t-6,t-4]}$ $\times$Move In From Low$_{[t-3,t-1]}$			-138.730*** (15.358)			
Tenured Leave$_{[t-6,t-4]}$ $\times$Move In From High$_{[t-3,t-1]}$				-10.231 (9.511)		
Tenured Move Out$_{[t-3,t-1]}$					0.659 (0.403)	
Tenured Move Out$_{[t-6,t-4]}$					0.283 (0.384)	
Untenured Move Out$_{[t-3,t-1]}$					0.241** (0.115)	
Untenured Move Out$_{[t-6,t-4]}$					0.540 (0.481)	
Move Up$_{[t-3,t-1]}$						0.318* (0.174)
Move Up$_{[t-6,t-4]}$						0.158 (0.275)
Move Down$_{[t-3,t-1]}$						0.750 (0.574)
Move Down$_{[t-6,t-4]}$						1.641* (0.918)
Rank	-0.255 (0.292)	-0.305 (0.299)	-0.302 (0.297)	-0.255 (0.295)	-0.278 (0.297)	-0.281 (0.297)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes
N	621	621	621	621	621	621
R^2	0.511	0.507	0.511	0.507	0.511	0.511

Table 13: Redistribution of Students

This table tests whether would-be entrepreneurs choose a different field or enroll at other universities once they observe AI faculty departures from a given university. In columns (1) and (2), we test whether students would be more likely to become an entrepreneur in other fields of information technology once hey observe AI faculty departures from a given university. The dependent variables are $ln(1+\text{IT Entrepreneur})$ and IT Entrepreneur in column (1) and (2), respectively, where IT Entrepreneur is defined in Table 1. In columns (3) and (4), for university j in year t, the dependent variable is the sum of the variable, AI Entrepreneurs defined in Table 1, from universities within a same ranking group in our sample in year t minus the variable, AI Entrepreneurs, from university j in year t. We divide the 69 North American universities in our sample into five ranking groups, based on the variable Rank defined in Table 1. In columns (5) and (6), for university j in year t, the dependent variable is the sum of the variable, AI Entrepreneurs defined in Table 1, within a region in year t minus the variable, AI Entrepreneurs, from university j in year t. It includes universities of our sample from 12 regions, which are Toronto, New England, Montreal, Southern California, Northern California, Chicago, New York, Northern Carolina, Pittsburgh, Vancouver, Nashville, and Washington DC. For all specifications, robust standard errors are clustered at the university city level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	IT Entrepreneur		Similar Rank		Same Region	
	OLS	Poisson	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Untenured Leave$_{[t-3,t-1]}$	0.039	2.451*	-0.639*	-0.059	-0.907	-0.031
	(0.801)	(1.423)	(0.357)	(0.457)	(0.726)	(0.667)
Untenured Leave$_{[t-6,t-4]}$	-0.168	0.063	0.076	0.045	0.183	0.978
	(0.259)	(0.320)	(0.200)	(0.234)	(1.135)	(0.859)
Tenured Leave$_{[t-3,t-1]}$	-0.257	1.069	-0.000	-0.151	0.326	-0.343
	(0.570)	(1.000)	(0.317)	(0.255)	(0.515)	(0.652)
Tenured Leave$_{[t-6,t-4]}$	-1.286**	0.339	-0.603	-0.231	-0.373	-0.723
	(0.501)	(1.058)	(0.440)	(0.274)	(1.034)	(1.586)
Rank	-0.197	-0.017	1.253***	1.215***	-0.734*	-1.362**
	(0.377)	(0.364)	(0.367)	(0.321)	(0.391)	(0.554)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes
N	621	621	621	621	306	306
R^2	0.655		0.768		0.778	

Table 14: Placebo Test - Entrepreneurs From Non-local Universities

This table tests whether an unobservable university's location-specific factors can confound our main results. The observation in this table is a city-year pair. The dependent variable is the number of entrepreneurs who establish AI startups in year t in city j but who are not alumni of universities located in city j. Specifications (1) and (3) are based on an OLS model with the dependent variable as the log of the total number of non-local entrepreneurs plus one. Specifications (2) and (4) are based on a poisson model with the dependent variable as the total number of non-local entrepreneurs. All regressors are the city-year average of variables defined in the Table 1. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	OLS (1)	Poisson (2)	OLS (3)	Poisson (4)
City Average Leave$_{[t-1,t-3]}$	1.093**	10.822		
	(0.514)	(7.977)		
City Average Leave$_{[t-4,t-6]}$	0.066	0.269		
	(0.383)	(9.641)		
City Average Tenured Leave$_{[t-1,t-3]}$			1.483*	37.922**
			(0.728)	(17.398)
City Average Tenured Leave$_{[t-4,t-6]}$			0.253	-15.436
			(0.449)	(46.261)
City Average Untenured Leave$_{[t-1,t-3]}$			-0.427	-4.024
			(0.734)	(6.782)
City Average Untenured Leave$_{[t-4,t-6]}$			-0.164	-11.761
			(0.570)	(11.486)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	147	147	147	147
R^2	0.281		0.291	
Pseudo R^2		0.409		0.437

Online Appendix

Figure OA1: AI Wage Gap
This graph shows median annual pay for AI graduates and general software engineering graduates based on H1B applicants.

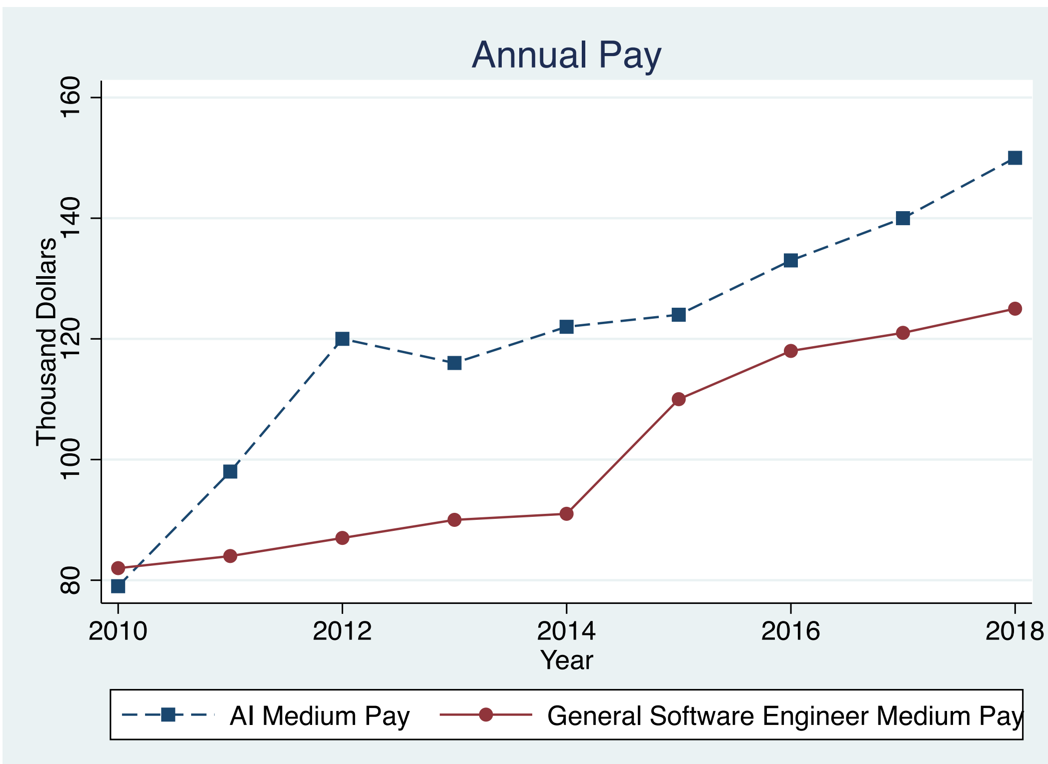

Table OA1: MBA Co-Founders

This table tests that, conditional on AI startup founders, whether the founders who are affected by AI faculty departures are more likely to have a co-founder who holds an MBA degree. The dependent variable, MBA Co-founder, is the natural log of one plus the number of co-founders who hold an MBA degree. All other variables are defined in Table 1. For all specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	ln(1+AI Entrepreneur)		
	OLS	OLS	OLS
	(1)	(2)	(3)
Untenured Leave$_{[t-1,t-3]}$	0.232	0.287	-0.028
	(0.339)	(0.340)	(0.336)
Untenured Leave$_{[t-4,t-6]}$	0.179	0.243**	0.113
	(0.134)	(0.142)	(0.149)
Tenured Leave$_{[t-3,t-1]}$	-0.130	-0.084	0.017
	(0.375)	(0.399)	(0.488)
Tenured Leave$_{[t-6,t-4]}$	0.421	0.456	1.487
	(0.476)	(0.496)	(1.138)
Rank	-0.201	-0.195	-0.200
	(0.157)	(0.159)	(0.177)
Tenured Leave$_{[t-6,t-4]}$ $\times$PhD		-0.398	
		(0.595)	
PhD		-0.078**	
		(0.040)	
Tenured Leave$_{[t-6,t-4]}$ $\times$STEM			-1.709
			(1.134)
STEM			-0.097**
			(0.045)
Year FE	Yes	Yes	Yes
University FE	Yes	Yes	Yes
N	363	363	363
R^2	.4	.42	.45

Table OA2: NSF Grant

This table tests whether AI faculty departures would have an effect on the number of NSF grant recipients at the universities from which they left. All variables are defined in Table 1. Column (1) is OLS regression and column (2) is poisson regression. For both specifications, robust standard errors are clustered at the city level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	ln(1+NSF)	
	OLS	OLS
	(1)	(2)
Untenured Leave$_{[t-3,t-1]}$	-0.354	-0.388
	(0.394)	(0.390)
Untenured Leave$_{[t-6,t-4]}$	-0.283	-0.319
	(0.226)	(0.247)
Tenured Leave$_{[t-3,t-1]}$	0.026	
	(0.364)	
Tenured Leave$_{[t-6,t-4]}$	0.041	
	(0.364)	
Rank	-0.274	-0.247
	(0.258)	(0.261)
Tenured Complete Leave$_{[t-3,t-1]}$		0.391
		(0.340)
Tenured Complete Leave$_{[t-6,t-4]}$		-0.422
		(0.347)
Year FE	Yes	Yes
University FE	Yes	Yes
N	531	531
R^2	0.548	0.551