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Artificial Intelligence, Education, and Entrepreneurship

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ABSTRACT

We document an unprecedented brain drain of Artificial Intelligence (AI) professors from universities from 2004 to 2018. We find that students from the affected universities establish fewer AI startups and raise less funding. The brain-drain effect is significant for tenured professors, professors from top universities, and deep-learning professors. Additional evidence suggests that unobserved city- and university-level shocks are unlikely to drive our results. We consider several economic channels for the findings. The most consistent explanation is that professors' departures reduce startup founders' AI knowledge, which we find is an important factor for successful startup formation and fundraising.

STARTUPS AND ENTREPRENEURSHIP ARE IMPORTANT for innovation, employment, and economic growth (e.g., Schumpeter (1942), King and Levine (1993)). In this paper, we study factors that increase entrepreneurship and help attract venture capital (VC) funding for Artificial Intelligence (AI) startups. AI startups are particularly important because of their exponential growth and high potential for creative destruction. According to the AI

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Index 2022 Annual Report (Zhang et al. (2022)), investment in global AI startups reached a record $93.5B in 2021, more than double the level of investment in 2020. AI has thus become one of the most promising and disruptive General Purpose Technologies (GPTs), with the potential to change every aspect of our lives and spur economic growth (Acemoglu and Restrepo (2018), Aghion, Jones, and Jones (2018), Cockburn, Henderson, and Stern (2018), Trajtenberg (2018)). Not surprisingly, the largest companies and countries in the world are fighting for leadership in AI. In 2016 Sundar Pichai, CEO of Google, stated that "In the next 10 years, we will shift to a world that is AI-first." In February 2019, the White House issued an executive order titled, "Maintaining American Leadership in AI."[1] World Economic Forum further observes that over a short period of time, AI has become "a key driver of the Fourth Industrial Revolution."[2] We study startups that are at the forefront of this revolution.

Our analysis is based on a novel sample of 432 AI startups founded by 504 AI entrepreneurs. Specifically, we focus on professors' importance in students' startup success. Our first contribution is to document an unprecedented brain drain of AI faculty from academia to industry.[3] The significant pay gap between industry and academia makes it virtually impossible for universities to retain their best AI professors. Top AI researchers Geoffrey Hinton and Yann LeCun, who won the 2018 Turing Award, were, respectively, hired by Google and Facebook to lead their AI labs. Geoffrey Hinton's student Ilya Sutskever received more than $1.9 million from OpenAI in 2016 (Metz (2018)). In addition to superior compensation packages, companies attract AI professors with superior computational resources, big data, and the ability to deploy professors' intellectual products at scale (Etzioni (2019)).

Our main contribution is to show that when AI professors leave academia, students in the affected universities establish fewer AI startups and raise less early-stage funding. From 2004 through 2018, there were 211 full or partial departures of AI faculty, with 149 AI professors taking industry jobs and the remaining 62 professors establishing AI startups. On the extensive margin, we find that a one-standard-deviation increase in our tenured AI brain-drain measure during period $[t-6, t-4]$ is associated with, on average, a nearly 5% decline in the number of future AI entrepreneurs who graduate in year t. Departures during period $[t-3, t-1]$ or those of untenured faculty do not show a significant effect. The negative effect that we document is more pronounced for students whose highest degrees are a master's or PhD and for departures of deep-learning professors or professors from

[1] See https://www.federalregister.gov/documents/2019/02/14/2019-02544/maintaining-american-leadership-in-artificial-intelligence.

[2] See World Economic Forum Report: https://www.weforum.org/platforms/shaping-the-future-of-technology-governance-artificial-intelligence-and-machine-learning.

[3] The term "brain drain" is typically used in the context of the immigration of highly skilled workers to another country (Kwok and Leland (1982)). In this paper, we use the term to describe the exodus of AI professors from academia to industry.

universities with computer science (CS) departments ranked in the top 10 in North America.[4]

We consider several possible explanations of these results. The main mechanism is that professors' departures reduce the AI knowledge that future founders can acquire at the university. Whether founders should be experts in AI to successfully establish an AI startup and raise funding is an open question. If AI entrepreneurs are jacks-of-all-trades with competencies in many management areas who can also raise funding and hire employees with deep AI knowledge, then the AI brain drain should not affect the number of AI startups formed by students of the affected universities. Moreover, given the prevalence of open-source AI software, research and code repositories, and online classes and communities for AI, whether founders' higher education in the field of AI is necessary for AI startup success is an open empirical question.

We find evidence that higher education associated with specialized knowledge helps students establish AI startups and attract funding from VCs. First, we show that the negative effect of the AI brain drain on startups is driven mainly by faculty departures that take place prior to students' enrollment. When professors leave after students' enrollment, there is an opportunity for some knowledge transfer, so the effect is weaker. Second, we find that the negative effect of the AI brain drain is most significant for tenured professors, professors from top universities, and deep-learning professors. Tenured faculty, especially at universities with a top-10 CS department, are more likely to be star professors with knowledge that students can use in their startups, whereas untenured faculty may leave academia because they have not received tenure and they are less likely to supervise PhD students. Deep learning is a novel field in machine learning that drives many recent innovations. The fact that the departures of deep-learning professors disproportionately affect startups suggests that AI professors are an important source of knowledge in this advanced area of AI. Any nonspecialized skill transfer from professors to students, such as leadership skills, should be unrelated to the type of technology used by startups. Also, our finding that PhD or master's students are most affected by the AI brain drain suggests that advanced knowledge of AI is important for entrepreneurial success.

On the intensive margin, we find that when tenured AI professors leave academia over period $[t-6, t-4]$, students who graduate from an affected university in year t raise less early-stage funding for their AI startups. Specifically, a one-standard-deviation increase in our tenured AI brain-drain measure for period $[t-6, t-4]$ is associated with, on average, a 20% drop in the total amount of early-stage funding, a \$1.66 million decline relative to our sample mean.[5] More recent faculty departures (i.e., one to three years prior to the

[4] Deep learning is a machine-learning technique that uses neural networks with a very large number of layers (LeCun, Bengio, and Hinton (2015)).

[5] Early-stage funding includes preseed, seed, and Series-A rounds. We focus on early-stage startups because, as of 2020, 77% of the AI startups in our sample were still in the early stage (i.e., no later than Series-A rounds).

entrepreneur's graduation) or departures by untenured faculty do not have a significant effect.

Our intensive-margin results suggest that access to funding depends on entrepreneurs' specialized knowledge. On average, the AI entrepreneurs in our sample start their new AI startups more than two years after graduation and receive their first external funding one year later. This time frame indicates that a significant gap exists between when professors leave and when students' startups receive funding. This long-term effect of the AI brain drain on funding can be explained by the reduction in the knowledge transfer from professors to students and by the importance of specialized academic knowledge for VC funding.

We explore several possible explanations for the negative effect of the AI brain drain on startups. The first is that after seeing AI professors leave for industry jobs, the best students enroll in a different university. To measure the quality of incoming students, we focus on PhD students because they are more likely to interact with faculty, and thus to respond to the brain drain, than are undergraduate and master's students. Our proxy for incoming PhD student quality is the number of prestigious AI fellowship recipients who enroll in a given university's PhD program in the same year and who receive fellowships within two years of enrollment. We do not find evidence that the AI brain drain affects a university's ability to attract talented PhD students.

Another explanation is that professors who leave for industry jobs, especially in the same city, might have VC connections that could benefit students. When professors leave, students lose these connections. We do not find, however, that the AI brain drain has a larger effect on startups in the same location as the university.

Would-be entrepreneurs following professors into industry is another possible explanation for the negative effect. Professors may take their best students with them to companies they join or the startups they establish. However, a number of findings suggest that this explanation is unlikely. First, we see a strong negative effect for departures four to six years prior to students' graduation and no effect for departures one to three years prior to graduation. These results suggest that professors are more likely to hire students who enrolled at the university after their departure than students they taught or worked with on research. It is also possible that departing professors hire students with a four- to six-year lag because it takes time for them to get promoted to management roles or to raise funding for their startups. The promotion effect should be less pronounced for top AI professors hired to manage AI labs at the largest companies. However, we find that the negative impact of the AI brain drain is more pronounced for tenured professors from top universities. The best students could also be hired by professors who establish their own startups. Inconsistent with this explanation, we find that the amount of funding raised by professors' startups closer to students' graduation year does not affect students' propensity to establish AI startups.

We next address potential unobservable shocks that could drive our results. First, we rule out time-varying, city-level shocks by showing that 87% of AI entrepreneurs establish AI startups in cities other than where their university is located. We also find that these nonlocal AI entrepreneurs are more affected by the AI brain drain than entrepreneurs whose AI startups are located in the same city as their university. It is, therefore, unlikely that city-level shocks drive our results. Second, we rule out time-varying, university-specific shocks, as we do not find evidence that the AI brain drain affects new startup creation or early-stage financing for non-AI startups in the information technology (IT) sector. This finding also suggests that the negative effects of the AI brain drain on AI startups are unlikely to be driven by would-be AI entrepreneurs switching to other IT fields.

We also consider the possibility that some unobservable time-varying demand factor leads to the AI brain drain from universities to companies and the subsequent hiring of graduates from the same universities. For example, the AI brain drain may increase university's visibility in the industry and result in higher demand for their graduates from companies looking to hire AI talent. In this case, students in affected universities face a higher opportunity cost to establish a startup leading to fewer AI startups being established. However, this channel cannot explain why the negative effect of the AI brain drain is more pronounced for the top universities, for which the visibility factor is less of a concern. It is also not clear why one to three years is not sufficient for companies to identify AI talent in a given university, and they need at least four to six years to bridge this informational friction.

Related Literature. Our paper contributes to several strands of the literature. First, we contribute to the entrepreneurship literature. Identifying the determinants of startup success is an important question from both positive and normative perspectives. Previous studies find that financing (Kaplan and Strömberg (2003), Hall and Lerner (2010), Kerr, Lerner, and Schoar (2011), Corradin and Popov (2015), Bernstein, Korteweg, and Laws (2017), Ersahin, Irani, and Waldock (2021)), work experience in tech firms (Gompers, Lerner, and Scharfstein (2005), Elfenbein, Hamilton, and Zenger (2010)), peer effects (Nanda and Sørensen (2010), Lerner and Malmendier (2013)), age (Azoulay et al. (2020)), and the founding team (Bernstein, Korteweg, and Laws (2017)) are important for startup creation. The literature on the role of entrepreneurs' knowledge for startup success is still developing. Kaplan, Sensoy, and Strömberg (2009) argue that a startup's business model is more important than management skills for startup success. Ewens and Marx (2018) document that VCs add value by replacing startup founders because the optimal management skills evolve over a startup's lifecycle. In a recent study based on Brazilian data, Bernstein et al. (2022) find that skilled entrepreneurs are more likely to form firms when local opportunities arise.

The key question that future entrepreneurs, educators, and policymakers want to see addressed is what type of skills are most important for entrepreneurs. In a seminal work, Lazear (2004) argues that entrepreneurs must have a general set of skills rather than expertise in any single skill. He finds that entrepreneurs are likely to study a varied MBA curriculum at the university, which is consistent with his balanced-skills theory of entrepreneurship. However, we find that this result cannot be generalized to all academic disciplines. The contribution of our paper is to show that founders' domain-specific knowledge gained via higher education is important for startup formation and funding. These findings are important for both future entrepreneurs and policymakers because they highlight the skills needed for entrepreneurial success in a data- and AI-driven economy.

Our paper also contributes to the literature on the spillover of university research to the private sector. Zucker, Darby, and Brewer (1998) study the emergence of the biotech industry around U.S. universities after the discovery of recombinant DNA in 1973. Hvide and Jones (2018) document a decline in entrepreneurship by university researchers when the rights to their innovations are reallocated to the university. In a recent paper, Babina et al. (2020) document that a university's funding source affects the intensity of entrepreneurship by its researchers in general and by professors in particular. We make several contributions to this literature. First, we provide the first systematic evidence on the AI brain drain. Second, we use the AI brain drain to show that advanced academic knowledge can have a significant effect on students' ability to establish AI startups and raise funding. Third, we compare the characteristics of professors' and students' startups to show that professors raise twice as much early-stage funding as do students with undergraduate degrees.

We also contribute to the emerging finance literature that studies AI.[6] Babina et al. (2023) document that investing in AI enables firms to grow faster in terms of both sales and employment. Moreover, they show that larger firms tend to make such investments, a potential factor in the rise of superstar firms. Grennan and Michaely (2020) present evidence that AI disrupts labor markets for security analysts. They find that analysts who cover stocks that are easier to analyze with AI are more likely to reduce their AI coverage and leave the profession. Bessen et al. (2022) survey AI startups in 2019 to study whether startups rely on a proprietary training data and how it correlates with their ability to attract funding. We contribute to this literature by presenting characteristics of AI entrepreneurs and by comparing key differences between AI and non-AI (IT) startups. Moreover, our methodology allows us to study both the creation of AI startups and the amount of funding they raise in each funding round between 2010 and 2020.

More broadly, our study of AI startups contributes to new literature that studies AI's impact on society and the economy. In a recent paper, Acemoglu and Restrepo (2018) develop a framework in which AI can have both a negative and a positive effect on the demand for labor. The negative effect is due to the displacement risk, while the positive effect results from improved productivity and higher capital accumulation. Korinek and Stiglitz (2017) and Guerreiro, Rebelo, and Teles (2022) discuss the channels through which AI can

[6] A growing literature uses deep learning and machine learning as a tool for finance applications (Heaton, Polson, and Witte (2017), Aubry et al. (2019), Chen, Pelger, and Zhu (2019), Gu, Kelly, and Xiu (2020), Erel et al. (2021)), but AI itself is not the focus of this literature. For example, Nagel (2021) provides deep analysis of machine-learning tools for asset pricing.

increase inequality and the best way to address this concern, while Aghion, Jones, and Jones (2018) study the implications of AI on economic growth. Our first contribution to this literature is to show that the scarcity of AI human capital is important for AI startups' innovation. This scarcity can also reduce labor-augmenting technical progress, increase inequality, and negatively impact opportunities for AI-driven economic growth. Our second contribution to this literature is to analyze the obstacles to AI startup formation and funding. Given the importance of innovation to the economy (Romer (1990)), these obstacles should not be overlooked.

Last, our paper contributes to the debate about the effect of tech giants on entrepreneurship. On the one hand, Babina and Howell (2020) document a knowledge spillover effect whereby corporate R&D leads to the company's employees establishing more startups. Jin (2020) shows that the prospect of getting funded or acquired by a tech giant has positive effects on entrepreneurship. On the other hand, Kamepalli, Rajan, and Zingales (2020) argue that big-tech platforms create a "kill zone" around their business. Our paper suggests that big-tech firms' poaching of AI professors can negatively affect entrepreneurship due to the reduction in knowledge diffusion from professors to students.

The outline of the paper is as follows. Section I describes data and summary statistics. Section II presents the empirical results. Section III discusses economic channels. Section IV concludes.

I. Data Description and Summary Statistics

A. AI Entrepreneurs and AI Startups

We collect information about entrepreneurs and startups from the Crunchbase database.[7] One of the advantages of Crunchbase over other commercial databases is its broad coverage due to crowdsourcing and data coverage from TechCrunch. As a result, the Crunchbase sample includes startups that are not VC financed, unlike the data from VentureXpert. Dalle, Den Besten, and Menon (2017) compare the coverage of Crunchbase with that of the OECD Entrepreneurship Financing Database and find that starting from 2010, the first year of our sample, Crunchbase has broader coverage in both the United States and other countries.

More importantly, relative to other databases, Crunchbase provides the most recent data about startups, including technology- or product-specific keywords. We classify a startup as an AI startup if it has at least one of the following keywords in the Crunchbase database: *artificial intelligence, machine learning, neural networks, robotics, face recognition, image processing, computer vision, speech recognition, natural language processing, autonomous driving, autonomous vehicle*, or *the semantic web*.

[7] According to the Kauffman Foundation, Crunchbase is "the premier data asset on the tech/startup world." Source: https://www.kauffman.org/microsites/state-of-the-field/topics/finance/equity/venture-capital.

Our sample includes 504 AI entrepreneurs and 1,531 non-AI (IT) entrepreneurs who graduated from 84 North American universities over the period 2010 to 2018. A graduate is identified as an AI entrepreneur if he or she starts an AI startup after receiving the highest degree in our sample. Non-AI entrepreneurs are founders of non-AI startups associated with Crunchbase keywords *information technology, software*, or *internet*, but with none of the keywords we use to identify AI startups. The 84 universities were selected such that at least one AI entrepreneur graduated from each of the universities between 2004 and 2009.[8] We begin the sample period in 2010 because there is a maximum six-year lag between our AI brain-drain measures and students' graduation. In total, these graduates founded or co-founded 432 AI startups and 1,394 non-AI (IT) startups. The AI startups innovate in the areas of cybersecurity, retail, early detection of breast cancer, solutions for the oil and gas industry, augmented reality, sleep therapy, and supply chain planning, among others.

One of the contributions of the paper is to compare AI startups and AI entrepreneurs to non-AI startups and non-AI entrepreneurs in other fields of the IT sector. In Table I, we compare the characteristics of 504 AI entrepreneurs with those of 1,531 non-AI entrepreneurs.

We find that AI entrepreneurs are 6% less likely to be single founders than non-AI entrepreneurs. AI entrepreneurs also tend to be better educated than non-AI entrepreneurs: one out of four AI entrepreneurs has a PhD degree, while PhD holders constitute only 9% of non-AI entrepreneurs. In fact, the whole distribution of academic degrees is shifted to the right for AI entrepreneurs. They are less likely to have only a bachelor's degree and more likely to have a non-MBA master's degree. AI entrepreneurs are also 3% less likely to have an MBA degree than non-AI entrepreneurs, suggesting that general management skills are not as important for AI entrepreneurs as domain-specific knowledge. This is also consistent with the finding that 31% of AI entrepreneurs studied CS in school versus 23% of non-AI entrepreneurs. We find that 18% of AI entrepreneurs graduated from a university with a top-10 CS department, as opposed to 7% for non-AI entrepreneurs. AI entrepreneurs are also more likely to graduate with a STEM (science, technology, engineering, and mathematics) degree than non-AI entrepreneurs. Taken together, these results above are consistent with the idea that specialized academic knowledge is needed to establish AI startups.

On average, an AI entrepreneur establishes a startup 2.42 years after graduation, which is slightly longer than the time it takes to establish a non-AI startup. Both types of entrepreneurs are less likely to establish a startup in the city where they went to college, suggesting that local connections do not seem to be particularly important for AI or IT entrepreneurs.

In Table II, Panel A, we compare the characteristics of 432 AI startups with those of 1,394 non-AI startups. We find that AI startups have, on average, slightly more cofounders than non-AI startups. Also, 28% of AI startups have

[8] In Section II.C, we show that our results are robust to various sample selection methods.

Table I

Summary Statistics at the Entrepreneur Level

This table compares the characteristics of AI entrepreneurs and non-AI entrepreneurs. AI entrepreneurs are founders of AI startups, and non-AI entrepreneurs are founders who establish IT-related startups excluding AI. The sample includes entrepreneurs who received their highest degree between 2010 and 2018 from the 84 universities in our sample and who started their firms after they received the degree. *Single Founder* is an indicator equal to one if a founder does not have a cofounder. *Bachelor*, *Master's (Non-MBA)*, *MBA*, and *PhD* are dummy variables that indicate entrepreneurs' highest degree. *Computer Science* and *STEM (Non-CS)* are dummy variables indicating the majors associated with entrepreneurs' highest degrees. *Top 10* is a dummy variable equal to one if entrepreneurs' highest degrees are obtained from North American universities with CS departments ranked in the top 10. *Found Lag* is the number of years between an entrepreneur's graduation year and startup inception year. *Local Founder* is an indicator equal to one if entrepreneurs start a new firm in the same city where the university from which they received their highest degree is located. *, **, and *** indicate that the difference is statistically significant at the 10%, 5%, and 1% level, respectively.

	N(AI)	N(IT)	Mean(AI)	Mean(IT)	AI - IT	SE
Single founder	504	1,531	0.19	0.25	-0.06^{***}	0.022
Bachelor	504	1,531	0.26	0.43	-0.17^{***}	0.025
Master (Non-MBA)	504	1,531	0.34	0.26	0.08^{***}	0.023
MBA	504	1,531	0.05	0.08	-0.03^{**}	0.013
PhD	504	1,531	0.26	0.09	0.17^{***}	0.017
CS major	504	1,531	0.31	0.23	0.08^{***}	0.022
STEM (Non-CS)	504	1,531	0.37	0.26	0.11^{***}	0.023
Top 10	504	1,531	0.18	0.07	0.11^{***}	0.015
Found lag	504	1,531	2.42	2.20	0.22^{**}	0.107
Local founder	504	1,531	0.13	0.15	−0.02	0.018

at least one founder with a PhD degree, as opposed to 9% for non-AI startups, and 20% of AI startups have at least one founder who graduated from a university with a top-10 CS department, as opposed to 7% for non-AI startups. In our sample, 367 AI startups (85%) versus 1,028 non-AI startups (74%) have secured some level of external funding. For startups that received external funding, information about funding amount and stage is available for 276 AI startups and 687 non-AI startups.

An average AI startup raised $8.32 million in the early stage of financing, including preseed, seed, and Series-A round financing. This is $3.54M more than the amount of funding raised by an average non-AI startup in the early stage. When we decompose the early-stage funding into seed rounds and series-A rounds, we see the same pattern: AI startups receive significantly more funding in each stage. Interestingly, it is not the case that AI startups raise more funding because they substantially delay fundraising—an average AI startup receives its first funding 10.4 months after establishment, compared to 9.4 months for non-AI startups.

In Table III, we report the number of AI entrepreneurs and non-AI entrepreneurs at the university-year level. On average, there are 0.667 AI entrepreneurs in each university-year, with a maximum of 11. The average

Table II

Summary Statistics at the Startup Level

This table presents summary statistics for AI startups and non-AI (IT) startups established by university graduates and AI startups founded by professors. Panel A compares the characteristics of AI startups and non-AI startups, both of which were founded by university graduates. In our sample, 367 AI startups (85%) and 1,028 non-AI startups (74%) received external funding. Relevant information about funding amounts and stages is available for 276 AI startups and 687 non-AI startups. *PhD* and *Top 10* are dummy variables equal to one if at least one founder in a startup holds a PhD degree and if the highest degree was obtained from a university with a top-10 CS department, respectively. *Early-Stage Startup* is an indicator equal to one if a startup received funding in rounds no later than the Series-A round in 2020. Panel B compares the characteristics of AI startups that were established by university graduates and by professors. All of the founders in columns (1), (2), and (3) of Panel B hold bachelor's, master's, and PhD degrees, respectively, as their highest degree. We do not include startups with cofounders holding different degrees. In column (4), all of the founders of AI startups are university professors who are part of our AI brain-drain sample. Of the 62 professor founders, we exclude 15 founders who cofounded AI startups with university students. Other variables are defined in the Appendix. *, **, and *** indicate that the difference is statistically significant at the 10%, 5%, and 1% level, respectively.

Panel A: AI versus Non-AI (IT)

	N(AI)	*N*(IT)	Mean(AI)	Mean(IT)	Diff.	SE
Number of founders	432	1,394	2.31	2.22	0.09	0.061
PhD	432	1,394	0.28	0.09	0.18***	0.018
Top 10	432	1,394	0.20	0.07	0.12***	0.016
Funding lag	367	1,028	0.87	0.79	0.08	0.065
Early-stage startup (%)	276	687	0.77	0.83	−0.06**	0.028
Early-stage financing ($MM)	276	687	8.32	4.78	3.54***	0.702
Preseed-round financing ($MM)	53	109	0.34	0.29	0.05	0.083
Seed-round financing ($MM)	187	541	2.48	1.44	1.04***	0.143
Series-A financing ($MM)	138	259	13.14	9.55	3.60***	1.289

Panel B: AI Startups by Founder Type

	Bachelor (1)	Master (2)	PhD (3)	Professor (4)	(2) - (1)	(3) - (1)	(4) - (1)
Seed-round ($MM)	1.77	2.85	2.56	2.91	1.08**	0.79**	1.14**
Seed-round age	1.41	1.70	1.34	1.48	0.29	−0.07	0.07
Series-A ($MM)	9.25	12.36	16.11	19.78	3.11	6.86*	10.53**
Series-A age	2.70	2.87	2.40	1.71	0.17	−0.30	−0.99**
Number of founders	2.28	2.29	2.21	2.27	0.01	−0.07	−0.01

number of non-AI entrepreneurs per university-year is two, with a maximum of 46. These estimates suggest that an average university produces one AI entrepreneur for every three non-AI entrepreneurs. The five universities with the most AI entrepreneurs graduating between 2010 and 2018 are Stanford University (125), MIT (113), University of California, Berkeley (59), Carnegie Mellon University (CMU) (56), and Harvard University (52). Figure IA.1 in the Internet Appendix provides the number of AI entrepreneurs for the other universities in the sample.[9]

[9] The Internet Appendix may be found in the online version of this article.

Table III
Summary Statistics at the University-Year Level

Each observation in the following table is a university-year pair. The variable t is between 2010 and 2018. The data include 84 universities. Lagged variables start as early as 2004. All variables are defined in the Appendix. All AI brain-drain measures and professor-startup funding measures are winsorized at the 1st and 99th percentiles.

	N	Mean	Median	*SD*	Min	Max
AI Entrepreneur$_t$	756	0.667	0.000	1.493	0.000	11.000
Non-AI Entrepreneur$_t$	756	2.025	1.000	3.842	0.000	46.000
AI Faculty$_t$	756	7.135	6.000	6.686	0.000	45.000
AI Brain Drain$_{[t-6,t-1]}$	756	0.010	0.000	0.019	0.000	0.083
AI Brain Drain$_{[t-3,t-1]}$	756	0.012	0.000	0.030	0.000	0.167
AI Brain Drain$_{[t-6,t-4]}$	756	0.006	0.000	0.018	0.000	0.083
Untenured AI Brain Drain$_{[t-6,t-1]}$	756	0.003	0.000	0.009	0.000	0.052
Untenured AI Brain Drain$_{[t-3,t-1]}$	756	0.003	0.000	0.011	0.000	0.067
Untenured AI Brain Drain$_{[t-6,t-4]}$	756	0.003	0.000	0.012	0.000	0.067
Tenured AI Brain Drain$_{[t-6,t-1]}$	756	0.006	0.000	0.015	0.000	0.083
Tenured AI Brain Drain$_{[t-3,t-1]}$	756	0.009	0.000	0.026	0.000	0.167
Tenured AI Brain Drain$_{[t-6,t-4]}$	756	0.003	0.000	0.012	0.000	0.067
Non-Deep-Learning Brain Drain$_{[t-6,t-1]}$	756	0.007	0.000	0.016	0.000	0.083
Non-Deep-Learning Brain Drain$_{[t-3,t-1]}$	756	0.009	0.000	0.026	0.000	0.167
Non-Deep-Learning Brain Drain$_{[t-6,t-4]}$	756	0.005	0.000	0.015	0.000	0.067
Deep-Learning Brain Drain$_{[t-6,t-1]}$	756	0.002	0.000	0.007	0.000	0.033
Deep-Learning Brain Drain$_{[t-3,t-1]}$	756	0.003	0.000	0.010	0.000	0.048
Deep-Learning Brain Drain$_{[t-6,t-4]}$	756	0.001	0.000	0.007	0.000	0.048
Professor-Startup Funding Raised$_{[t-3,t-1]}$	756	5.766	5.000	4.752	5.000	46.600
Professor-Startup Funding Raised$_{[t-6,t-4]}$	756	11.168	11.000	1.213	11.000	21.000

B. AI Brain Drain

The second contribution of our paper is to document the AI brain drain from academia to industry. To do so, we develop AI brain-drain measures, hand-collect data about AI professors' affiliations to compute the measures, and use the measures to document an unprecedented AI brain drain between 2004 and 2018.

B.1. Measuring AI Brain Drain

To measure the AI brain drain at the university-year level, we first collect data about the number of AI professors who left a university partially or fully in a given year. We then compute the ratio of the number of AI professors who left the university to the total number of AI professors in the same year. In last step, we average this ratio over a three- or six-year period. Our measure is computed relative to the graduation year of the students (t).

The measure *AI Brain Drain*$_{[t-6,t-1]}$ is the AI brain drain over a six-year window, computed one to six years prior to students' graduation. To investigate economic channels, we compare two additional AI brain-drain measures: *AI Brain Drain*$_{[t-3,t-1]}$ is the average AI brain drain one to three years prior to students' graduation year, and *AI Brain Drain*$_{[t-6,t-4]}$ is the average AI brain drain four to six years prior to students' graduation year. We use a rolling window to account for the fact that it is difficult to measure a professor's departure year precisely, as some professors can take a leave of absence before they officially leave while others develop their own AI startups while still employed by a university.

We also compute the AI brain-drain measure for tenured and untenured faculty separately because untenured professors might leave involuntarily. In total, for our benchmark results, we use nine AI brain-drain measures that capture the type of AI professor departure (all, tenured, or untenured) and the time period relative to the students' graduation year ($[t-6, t-1]$, $[t-6, t-4]$, $[t-3, t-1]$).

B.2. Data

To compute our AI brain-drain measures, we need to know the total number of AI professors in each university in a given year. We take the total AI faculty size from CSRankings.org, which relies on the publications database DBLP and only counts tenure-track or tenured professors.[10] Table III reports that, on average, there are seven AI faculty in a given university in a given year, with a median of six and a maximum of 45.

To compute the number of AI faculty who leave universities, we hand-collect data from AI professors' LinkedIn profiles. To identify AI professors on LinkedIn, we employ two search methods. The first involves directly searching Google with inputs such as: site:linkedin.com/in/ "Professor" and "Artificial Intelligence" or "Machine Learning" or "Deep Learning" or "Natural Language Processing" or "Computer Vision" or "Autonomous Driving." Our second method is to search LinkedIn using reviewers' and program committee members' names from AI-related conferences. We extract 7,650 names of reviewers and committee members in the three largest conferences in the fields of machine learning and AI (International Conference on Machine Learning (ICML), Neural Information Processing Systems (NeurIPS), and Association for the Advancement of Artificial Intelligence (AAAI)), using data from 2008 to 2018. By adding names to our keyword searches, we can identify additional AI professors who were missed in the Google search. The two methods together lead 14,532 LinkedIn profiles.[11]

It is worth noting that both the total number of AI faculty obtained from CSRankings.org and our LinkedIn sample include professors from non-CS departments (e.g., mathematics and robotics) who do AI-related research. CSRankings.org relies on publications to identify AI professors, and it is quite

[10] The webpage https://dblp.org/faq provides information about the publications database used by CSRankings.org.

[11] In Section I of the Internet Appendix, we conduct case studies to examine the coverage of our LinkedIn sample for AI professors of four universities. The average coverage rate for the four universities is 71%.

common for professors from non-CS departments to publish papers related to AI. For our LinkedIn search, we did not impose any restrictions on professors' departments.

As we only consider tenured or tenure-track faculty, we exclude people with titles such as "Adjunct Professor," "Clinical Professor," and "Research Professor." Given that a tenured professor who left a full-time academic job may continue to work part time as an "Adjunct Professor," we ensure that only profiles of people who have never been tenure-track or tenured professors are excluded in this step. This step reduces the number of LinkedIn profiles to 4,086.

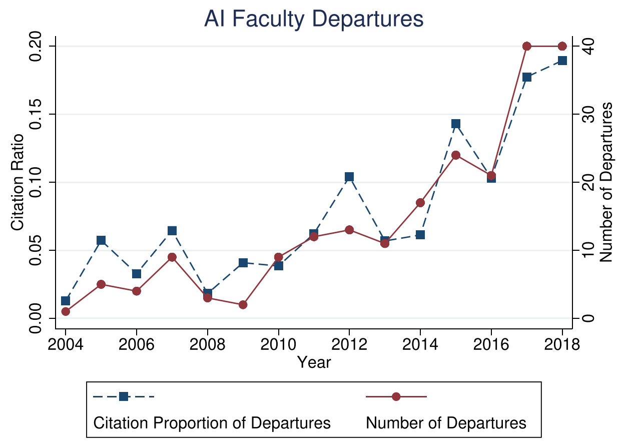
We next examine all the remaining LinkedIn profiles for changes in affiliation from a university to a company (complete leave) or for an additional affiliation with a company (partial leave). We record the date of the departure as the first date of the industry affiliation. The final sample includes 211 tenure-track and tenured AI faculty in North American universities who started to work for a private company (149) or established a startup (62) between 2004 and 2018. This sample includes 141 faculty who left their academic positions completely and 70 faculty who retained their university affiliations.

To compute AI brain-drain measures for tenured and untenured professors separately, we classify assistant professors as untenured faculty and associate or full professors as tenured faculty. The AI brain-drain sample comprises 143 tenured and 68 untenured faculty. We also manually classify faculty into those who work in the field of deep learning—a powerful machine-learning methodology that has fueled the recent AI revolution—and those who use more traditional machine-learning methods. To do so, we analyze each faculty's website and Google Scholar page. We classify faculty as deep-learning professors if they have published papers that use deep neural networks, such as recurrent or convolutional neural networks, or that develop new deep-learning techniques. We find that the deep learning methodology is general and can be used or developed by professors in different subfields of AI, such as robotics, self-driving cars, computer vision, and natural language processing. Our classifications suggest that 43% of all AI professors who left academia are deep-learning professors. Out of the 91 deep-learning professors who left academia, 77% are tenured. Given the high potential of the deep learning technology, it is not surprising that companies would try to hire tenured deep learning professors like Yann LeCun and Geoffrey Hinton to lead their AI research labs.

B.3. AI Brain-Drain Trends

Figure 1, Panel A shows the aggregate trend of the AI brain drain between 2004 and 2018. In our sample, only one AI professor left academia in 2004, whereas 40 left completely or partially in 2017 and 2018. Overall, there is an upward trend in the number of AI professors leaving academia between 2004 and 2018. Table III reports key summary statistics for the main AI brain-drain measures that we use in our regressions. We winsorize these measures at the 1^{st} and 99^{th} percentiles.

Panel A: AI Faculty Departures



Panel B: Departures by University

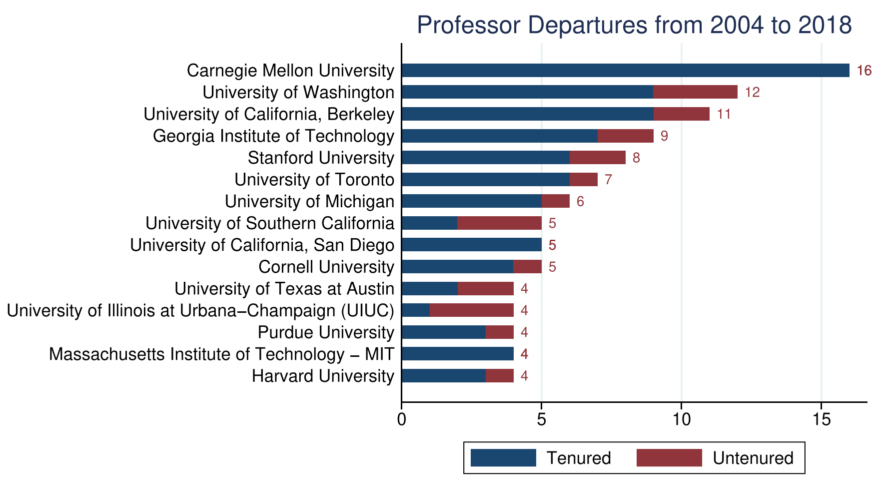


Figure 1. AI brain drain from university. Panel A shows the number of tenure-track and tenured AI professor departures during 2004 to 2018, along with the citation ratio, which is the sum of citations (captured at the time of departure) from AI faculty who left for industry divided by the sum of citations from all AI faculty for each year and each university. We then take the average across universities for each year. Panel B shows North American universities with the largest numbers of tenure-track or tenured AI professors who reported an industry position during 2004 to 2018.

To get a better understanding of the importance of AI faculty departures in terms of research influence, we compute the ratio of the total number of Google citations of the faculty who leave a university in a given year to the total number of Google citations of all faculty from that university that appear in our LinkedIn sample of 4,086 AI professors. In this calculation, we focus on universities with at least one faculty departure. The left axis in Figure 1, Panel A shows that between 2005 and 2011, departing professors accounted for around 5% of all citations by AI professors in their respective universities. However, by 2018 the ratio had increased to almost 19%. We conclude that the AI brain drain has become more important over the years, in terms of both the number of professors leaving academia and in terms of the academic influence of the departing professors.

Figure 1, Panel B shows the top 13 North American universities in terms of the number of faculty who took industry positions or established their own startups from 2004 to 2018. The three universities that lost the most AI faculty are CMU, the University of Washington, and UC Berkeley. CMU lost 16 tenured faculty members and no untenured faculty, while the University of Washington lost eight tenured and four assistant professors.

Figure 2 presents the "destinations" of the AI brain drain. Of the 211 AI professors leaving academia partially or fully, 62 established an AI startup, and the rest started full-time or part-time jobs at private companies. From 2004 to 2018, Google and its subsidiary DeepMind together hired 22 tenure-track and tenured AI professors from North American universities. Amazon and Microsoft hired 16 and 12 AI professors, respectively. Apart from technology firms, we also see that large firms from the finance industry, such as Morgan Stanley, American Express, and JP Morgan, poach AI professors. Publicly traded firms constitute 64% of all firms that hired AI professors.

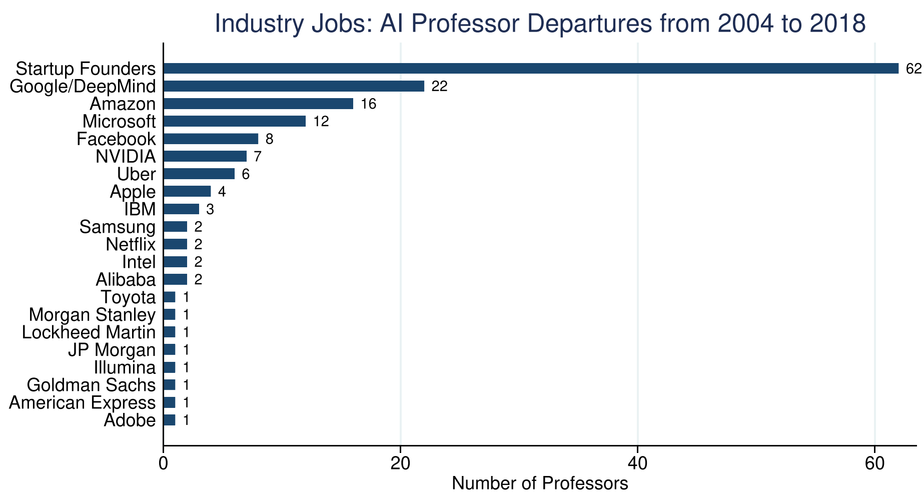
B.4. AI Professors' Startups

Of the 211 AI professors who left academia, 62 established AI startups.[12] In Table II, Panel B, we report the difference between professors' startups and students' startups. We divide students' startups into three categories: (i) startups founded by entrepreneurs who have an undergraduate degree, (ii) startups founded by entrepreneurs who have a master's degree, and (iii) startups founded by entrepreneurs who have a PhD degree. To get a clean comparison between the categories, we exclude startups with cofounders who have heterogeneous educational levels. We also exclude 15 startups founded by an AI professor and a cofounder who is not a professor.

Panel B shows that professors' startups raised 64% more funding in the seed round than startups founded by students with a bachelor's degree. The difference in funding is $1.14M, significant at the 5% confidence level. There is also an economically significant difference between the funding of professors' startups and that of master's students' startups and a smaller positive difference between professors' startups and PhD students' startups. Both PhD and master's students' startups raised significantly more funding relative to bachelor's students' startups. There is no significant difference in the number of founders, or in the age of professors' and students' startups, at the time they received the seed funding.

[12] There is no overlap between professors' startups and students' startups.

Panel A: AI Professors' Industry Jobs



Panel B: AI Brain Drain from University to Industry

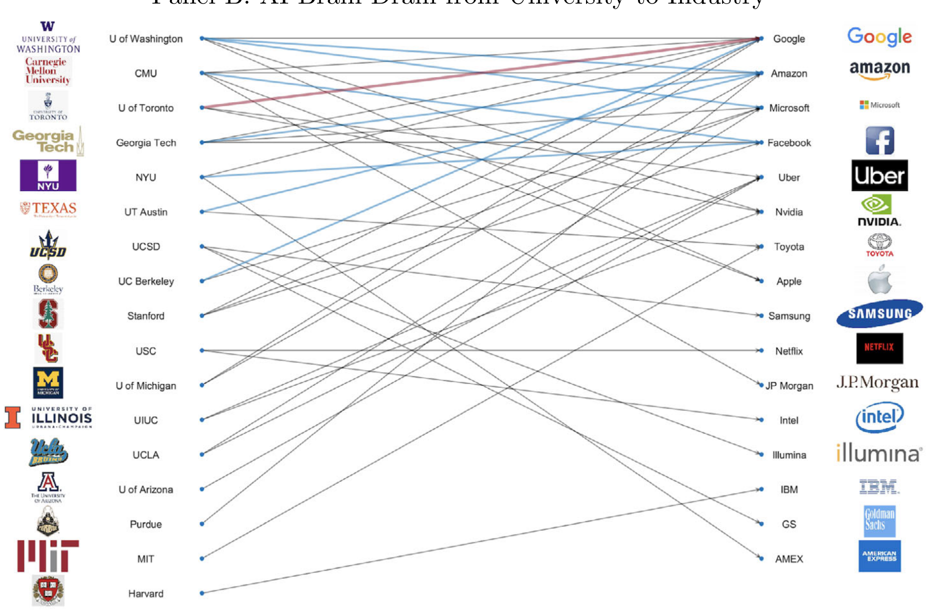


Figure 2. AI brain drain to industry. Panel A lists publicly traded firms that hired full-time or part-time AI professors during 2004 to 2018. Panel B shows the universities, from which those public firms hired AI professors. Black, blue, and red lines indicate that one, two, and three professors, respectively, were hired by a given public firm from a given university between 2004 and 2018.

For the Series-A funding round, there is a monotonic increase in funding as we compare startups whose founders have a bachelor's degree ($9.25M), those whose founders have a master's degree ($12.36), those whose founders have a PhD degree ($16.11), and those established by AI professors ($19.78M). The difference between the funding that professors' startups attract in Series-A and the funding that bachelor's students' startups receive in Series-A is $10.53M, a more than 100% increase. This difference is significant at the 5% level. One concern might be that professors' startups raise money later, so their Series-A round is larger. However, we find that professors' startups are much younger than bachelor's students' startups at the time they raise Series-A round funding.

The positive relationship between academic knowledge and AI startup funding is a novel empirical regularity that contributes to the entrepreneurial finance literature. In a recent paper, Roche, Conti, and Rothaermel (2020) find that biomedicine startups established by professors raise as much funding as biomedicine startups established by founders who are not professors. If academic expertise increases AI startups fundraising, it is important to investigate how the AI brain drain affects the ability of students to establish AI startups and raise funding.

B.5. Why Do AI Professors Leave Academia?

The AI brain drain is unlikely to be driven by internal factors in academia. We find that AI professors' startups raise $23 million on average in less than two years, with 20% of professors' startups acquired on average 3.5 years after their founding. This upside is likely to attract many AI professors to establish their own startups, especially if they can keep a tenured position at the university.

Another likely trigger to leave academia is the millions of dollars in compensation offered to AI professors by corporations (e.g., Metz (2017, 2018)). The corporate poaching of AI faculty has raised public concerns about its negative impact on universities (e.g., Economist (2016), Sample (2017)). According to Yoshua Bengio, one of the 2018 Turing Award winners and a professor at the University of Montreal, "That raises significant issues for universities and governments. They also need AI 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" (Metz (2017)).

In a recent Bloomberg op-ed, Ariel Procaccia, a CS professor at CMU, similarly asked, "If industry keeps hiring the cutting-edge scholars, who will train the next generation of innovators in artificial intelligence?" (Procaccia (2019)). This question provides a stage for our further analysis of the AI brain drain and students' AI startups.

II. AI Brain Drain and Entrepreneurship

A. The Creation of AI Startups (Extensive Margin)

We start with extensive margin analyses at the university level. Specifically, we test whether AI professors' departures from a university for an industry job affect the number of AI startups established by students who graduated from that university. We start with the following panel OLS specification:

$$\ln(1 + \mathit{AI\ Entrepreneur}_{j,t}) = \alpha_t + \theta_j + \beta \mathit{AI\ Brain\ Drain}_{j,[t-6,t-1]} + \phi \mathit{Rank}_{j,t} + \epsilon_{j,t}, \tag{1}$$

where α_t denotes graduation year fixed effects, θ_j denotes university fixed effects, $\mathit{AI\ Entrepreneur}_{jt}$ captures the number of graduates who graduate from university j in year t and found AI startups, and β captures the effect of $\mathit{AI\ Brain\ Drain}_{[t-6,t-1]}$ on students' ability to start AI firms after they graduate. We test additional specifications in which we use eight granular AI brain-drain measures, which helps us decompose the total AI brain drain into subcategories and study the type of AI brain drain that matters most.

Because of the average 2.4-year lag between graduation and startup inception, graduates in 2018 have mechanically fewer AI entrepreneurs than graduates in 2010. We control for this pattern by adding time fixed effects. This also allows us to focus on cross-sectional differences between universities. Even if all universities produce more AI entrepreneurs over time, we are interested in whether the increase is smaller for universities with higher AI brain drain.

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. We also control for computer department ranking (*Rank*) from CSrankings.org to account for time-series variation in university quality.[13]

The timeline below shows the timing between the graduation year (t) and AI brain drain. There are two periods for AI brain drain: four to six years prior to students' graduation and one to three years prior to graduation. Students are much more likely to interact with professors with whom they have an overlap during their studies. By looking separately at these two periods, we can rule out different explanations for our findings.

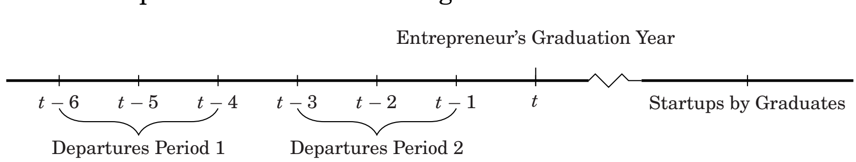


Table IV reports the OLS results of the estimation of equation (1). In column (1), we do not control for $\mathit{Rank}_{j,t}$, a university's CS department time-varying rank, whereas in column (2) we include it as a control variable. The

[13] See http://csrankings.org/faq for detailed information about the ranking methodology.

Table IV

Extensive Margin: University-Level Analysis

In this table, we show the effects of AI professors' departure for industry on entrepreneurship by university graduates. The sample includes AI and non-AI (IT) entrepreneurs who graduated between 2010 and 2018 and established startups after their graduation. The dependent variable *AI Entrepreneur*, for the OLS model in columns (1) to (5), is the natural log of one plus the number of AI entrepreneurs who graduated in year t from a given university. The dependent variable *Non-AI (IT) Entrepreneur*, for the OLS model in columns (6) to (10), is the natural log of one plus the number of entrepreneurs in the IT sector but not in the AI area who graduated in year t in a given university. Other variables are defined in the Appendix. All the dependent and independent variables are winsorized at the 1st and 99th percentiles. For all specifications, robust standard errors are clustered at the city level (i.e., the city where the entrepreneurs' alma mater is located) and are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	AI Entrepreneur					Non-AI (IT) Entrepreneur				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AI Brain Drain$_{[t-6,t-1]}$	−2.308**	−2.289**				−1.500	−1.475			
	(0.990)	(0.979)				(1.873)	(1.848)			
AI Brain Drain$_{[t-3,t-1]}$			−1.079*					−0.735		
			(0.546)					(1.055)		
AI Brain Drain$_{[t-6,t-4]}$			−1.929**					−0.800		
			(0.830)					(1.434)		
Untenured AI Brain Drain$_{[t-6,t-1]}$				−1.746					−2.273	
				(3.189)					(3.700)	
Tenured AI Brain Drain$_{[t-6,t-1]}$				−2.596**					−1.348	
				(1.270)					(2.530)	
Untenured AI Brain Drain$_{[t-3,t-1]}$					−2.811					−4.154
					(2.193)					(2.804)
Untenured AI Brain Drain$_{[t-6,t-4]}$					0.157					1.233
					(1.848)					(1.645)
Tenured AI Brain Drain$_{[t-3,t-1]}$					−0.823					−0.136
					(0.578)					(1.254)
Tenured AI Brain Drain$_{[t-6,t-4]}$					−3.901***					−2.998
					(1.065)					(2.385)
Rank Control	N	Y	Y	Y	Y	N	Y	Y	Y	Y
Graduation Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	756	756	756	756	756	756	756	756	756	756
Adj. R^2	0.567	0.569	0.570	0.569	0.573	0.645	0.648	0.647	0.647	0.651

coefficients on *AI Brain Drain*$_{[t-6,t-1]}$ in both columns (1) and (2) are negative and statistically significant at the 5% level.[14] When we seperate *AI Brain Drain*$_{[t-6,t-1]}$ into *AI Brain Drain*$_{[t-6,t-4]}$ and *AI Brain Drain*$_{[t-3,t-1]}$ in column (3), we find that the coefficient on *AI Brain Drain*$_{[t-6,t-4]}$ is negative and statistically significant at the 5% level. The coefficient on *AI Brain Drain*$_{[t-3,t-1]}$ is also negative, but the economic and statistical significance are smaller.

In column (4), we examine the impacts of tenured and untenured faculty separately. Untenured faculty leaving for an industry job has no effect, but departures by tenured professors have a statistically significant effect. In terms of economic significance, the coefficient on *Tenured AI Brain Drain*$_{[t-6,t-1]}$ is -2.596 in column (4), which implies that a one-standard-deviation increase in *Tenured AI Brain Drain*$_{[t-6,t-1]}$, 0.02, leads to about a 5% drop in the number of future AI entrepreneurs who graduate in year t.

In column (5), we further separate both *Tenured AI Brain Drain*$_{[t-6,t-1]}$ and *Untenured AI Brain Drain*$_{[t-6,t-1]}$ into two windows, $[t-6, t-4]$ and $[t-3, t-1]$. The regression results show that the coefficient on *Tenured Brain Drain*$_{[t-6,t-4]}$ is negative and statistically significant at the 1% level, whereas the coefficients on *Tenured Brain Drain*$_{[t-3,t-1]}$, *Untenured AI Brain Drain*$_{[t-6,t-4]}$, and *Untenured AI Brain Drain*$_{[t-3,t-1]}$ are all statistically insignificant. These results suggest that tenured AI faculty departures that take place in $[t-6, t-4]$ have the most significant impact on students' propensity to become AI entrepreneurs after they graduate. Overall, the results in columns (1) to (5) show that AI faculty departures to industry have a long-lasting negative effect on AI startup formation.

In columns (6) to (10), we examine whether AI faculty departures affect students' propensity to establish non-AI startups in the IT sector after they graduate. The dependent variable is the natural log of one plus the number of non-AI entrepreneurs who graduate in year t at a given university. Other than the dependent variable, the regression specifications in columns (6) to (10) are the same as those in columns (1) to (5). The results show that none of the coefficients on our nine AI brain-drain measures is statistically significant, suggesting that the AI brain drain has no impact on future non-AI entrepreneurship in the IT sector by university graduates. This finding implies that the negative effect is unlikely to be driven by would-be AI entrepreneurs switching to other IT fields. It also suggests that the effect is unlikely to be driven by some unobservable university- or city-level shocks because such shocks would affect non-AI entrepreneurs as well. In general, it is important to emphasize that only 13% of AI entrepreneurs establish a startup in the same city as the university from which they graduated with the highest degree. Therefore, it is unlikely that university- or local-level shocks contribute to the negative effect.

[14] Robust standard errors are clustered at the university city level because we cannot assume that two observations in the same city are independent.

To further rule out the possibility that city-level shocks drive the results, in Table IA.II of the Internet Appendix we test whether students who established a startup in the same city in which they studied are more affected by the AI brain drain than students who graduated from nonlocal programs and established startups locally. We find that nonlocal entrepreneurs are more affected by the AI brain drain than local entrepreneurs. Therefore, it is unlikely that university- or city-level shocks are driving the benchmark results.

B. Early-Stage Entrepreneurial Financing (Intensive Margin)

We next study the relationship between the AI brain drain and funding of students' startups. The intensive-margin results complement the extensive margin analysis, as they shed light on the importance of academic knowledge for fundraising.

Specifically, we study early-stage funding, defined as the aggregate funding received from preseed, seed, and Series-A rounds. The choice to focus on early-stage financing and to aggregate the early rounds is driven by data availability.[15] As with the extensive margin analysis, we compare AI startups' and non-AI startups' funding.

We use the following OLS model to test the effects of faculty departures on students' ability to attract startup funding:

$$\begin{aligned}\ln(\textit{Early Funding}_{i,j,t,\tau}) = \theta_j + \lambda_\tau + \delta_i + \beta \textit{AI Brain Drain}_{j,[t-6,t-1]} \\ + \phi \mathbf{X_{i,j,t}} + \epsilon_{i,j,t},\end{aligned} \tag{2}$$

where the dependent variable, $\textit{Early Funding}_{i,j,t,\tau}$, is the total funding amount from financing rounds no later than the Series-A round for startup j established in year τ by university graduate i who graduated in year t, θ_j denotes the startup location (city) fixed effects, λ_τ denotes startup founding year fixed effects, and δ_i denotes founder university fixed effects. The control variables, $\mathbf{X_{i,j,t}}$, include the university's CS department rank, whether the founder holds a PhD degree or master's degree, whether the founder's major is in CS or other STEM majors, the number of founders, and the number of investors. Robust standard errors are double clustered at the startup city and university city levels.

Table V shows the effects of AI faculty departures on both AI and non-AI startups' early-stage funding. The OLS results in column (1) show the effect of AI faculty departures on AI startups' early-stage funding without the control variables but with university, founding city, and founding year fixed effects. The results in column (2) include the control variables. The coefficients on $\textit{AI Brain Drain}_{[t-6,t-1]}$ in both columns (1) and (2) are negative and statistically significant at the 5% level. When we separate $\textit{AI Brain Drain}_{[t-6,t-1]}$

[15] According to Table II, Panel A, 77% of the AI startups in our sample are still in the early stage (i.e., no later than the Series-A round).

Table V

Intensive Margin: Early-Stage Funding

In this table, we test whether faculty departures affect the entrepreneurial financing of startups by university graduates. Each observation is a founder-startup pair and the sample includes entrepreneurs who received their highest degree between 2010 and 2018 and who started firms after they received the degree. The dependent variable is the natural log of the sum of all early-stage funding amounts. Early-stage rounds are defined as the preseed, seed, and Series-A rounds. Control variables include the following variables: a dummy indicating whether a startup has a founder with a PhD degree, a dummy indicating whether a startup has a founder with a master's degree, a dummy indicating whether a startup has a founder with a CS major, a dummy indicating whether a startup has a founder with a non-CS STEM major, the number of founders, and the CS department ranking. Founding City FE indicates fixed effects based on the city where startups are founded. Founding Year FE represents fixed effects based on the year of startup inception. Other variables are defined in the Appendix. All dependent and independent variables are winsorized at the 1st and 99th percentiles. For all specifications, robust standard errors are clustered at both the startup and university city levels and are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	AI Startup					Non-AI (IT) Startup				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AI Brain Drain$_{[t-6,t-1]}$	−18.980**	−16.276**				−1.297	2.887			
	(8.018)	(7.064)				(8.460)	(7.040)			
AI Brain Drain$_{[t-3,t-1]}$			−4.725					3.745		
			(4.280)					(3.859)		
AI Brain Drain$_{[t-6,t-4]}$			−18.806***					−3.601		
			(5.595)					(4.560)		
Untenured AI Brain Drain$_{[t-6,t-1]}$				49.968					−11.685	
				(41.552)					(15.295)	
Tenured AI Brain Drain$_{[t-6,t-1]}$				−21.790***					7.602	
				(6.319)					(6.754)	
Untenured AI Brain Drain$_{[t-3,t-1]}$					24.453					1.746
					(20.430)					(13.911)
Untenured AI Brain Drain$_{[t-6,t-4]}$					13.801					−9.871
					(20.659)					(6.496)
Tenured AI Brain Drain$_{[t-3,t-1]}$					−7.902**					5.019
					(3.600)					(3.393)
Tenured AI Brain Drain$_{[t-6,t-4]}$					−18.920***					0.225
					(5.821)					(4.843)

(*Continued*)

Table V—*Continued*

	AI Startup					Non-AI (IT) Startup				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls	N	Y	Y	Y	Y	N	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Founding City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Founding Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	238	238	238	238	238	616	616	616	616	616
Adj. R^2	0.192	0.237	0.244	0.248	0.246	0.108	0.238	0.238	0.238	0.237

into *AI Brain Drain*$_{[t-6,t-4]}$ and *AI Brain Drain*$_{[t-3,t-1]}$ in column (3), the coefficient on *AI Brain Drain*$_{[t-6,t-4]}$ is negative and statistically significant at the 1% level. The coefficient on *AI Brain Drain*$_{[t-3,t-1]}$ is also negative but economically and statistically insignificant. The negative effect is fully driven by tenured professors' departures, as can be seen in column (4). Departures by tenured professors have a negative effect at the 1% level, while the coefficient on untenured faculty departures is indistinguishable from zero. In column (5), we further break down both *Tenured AI Brain Drain*$_{[t-6,t-1]}$ and *Untenured AI Brain Drain*$_{[t-6,t-1]}$ into two windows, $[t-6, t-4]$ and $[t-3, t-1]$. The regression results show that the coefficient on *Tenured Brain Drain*$_{[t-6,t-4]}$ is negative and statistically significant at the 1% level. The coefficient on *Tenured Brain Drain*$_{[t-3,t-1]}$ is also negative at the 5% confidence level. The coefficients on *Untenured AI Brain Drain*$_{[t-6,t-4]}$ and *Untenured AI Brain Drain*$_{[t-3,t-1]}$ are indistinguishable from zero.

In terms of economic significance, the coefficient on *Tenured AI Brain Drain*$_{[t-6,t-4]}$ is −18.92 in column (5), which implies that a one-standard-deviation increase in *Tenured AI Brain Drain*$_{[t-6,t-4]}$, 0.012, leads to about a 20% ($=1 - e^{-18.92*0.012}$) decline in early-stage funding of AI startups founded by entrepreneurs who graduate in year t, representing a \$1.66 million dollar drop relative to our sample mean. For tenured faculty departures in the $[-3, -1]$ window, the negative effect is 17% ($=1 - e^{-7.09*0.026}$), representing a \$1.41 million dollar drop relative to our sample mean. In Table IA.VII of the Internet Appendix, we show that when we exclude master's students from the regression, only the coefficient on *Tenured AI Brain Drain*$_{[t-6,t-4]}$ is significant with the point estimate almost unchanged, while the coefficient on *Tenured AI Brain Drain*$_{[t-3,t-1]}$ becomes insignificant. Tenured professors who leave one to three years prior to master's students' graduation are unlikely to have a significant overlap with master's students because master's programs are usually one or two years long. This means that the negative effect of the AI brain drain on students' fundraising is mostly driven by tenured faculty departures that took place prior to students' enrollment in the program.

In Table V, columns (6) to (10), we examine whether AI faculty departures affect early-stage funding of non-AI startups in the IT sector. The coefficients on all nine of the AI brain-drain measures are statistically insignificant, suggesting that AI faculty departures do not influence students' ability to raise early-stage funding when they establish non-AI startups. We conclude that the negative effect of the AI brain drain on AI startups is not driven by university- or city-level shocks because these shocks would also affect non-AI startups. Moreover, if some unobservable university- or city-level shock would trigger AI faculty departures and also a later decline in fundraising by students' AI startups, more recent departures would show a more significant effect than the departures 10 years prior to startup funding. We find the opposite, which suggests that unobservable university-level or city-level shocks are unlikely to drive the results.

C. Robustness Checks

Since our AI brain-drain measures and the number of AI entrepreneurs at the university-year level are skewed and sparse, we winsorized them at the 99th percentile in the previous analyses. In this section, to further address concerns about a few outliers affecting our results, we conduct a battery of robustness checks. First, we test the robustness of the results with respect to the AI brain-drain measures. In Tables IA.III and IA.IV of the Internet Appendix, we use indicator variables measuring the departures of AI professors and reexamine the extensive-margin and intensive-margin results, respectively. Specifically, we replace the nine continuous AI brain-drain measures with indicators equal to one if the corresponding continuous measure is greater than zero. Both the extensive-margin and intensive-margin results are qualitatively unchanged compared to the results based on the continuous AI brain-drain measures.

For the number of AI entrepreneurs, one potential concern with the benchmark results is that the log-number of AI startups per university-year is sparse. To address this issue, we use inverse hyperbolic sine transformation as an alternative to log transformation. The results, which appear in Table IA.V of the Internet Appendix, are qualitatively unaffected.

We also test the robustness of the results with respect to the university selection approach. Our benchmark results rely on a sample of 84 universities that have at least one AI entrepreneur who graduated before 2010. This condition allows us to reduce noise in the estimation because most universities do not have a single AI professor. An alternative approach of selecting only universities with a given number of AI faculty results in a smaller sample. In Table IA.VI, columns (1) to (5), of the Internet Appendix, we show that the results continue to hold if we focus our analysis on university-years with at least one, two, three, four, and five AI professors, respectively. The AI brain-drain measures in Panel A are continuous, while the measures in Panel B are indicators. The coefficients in Panels A and B on *Tenured AI Brain Drain*$_{[t-6,t-4]}$ continue to be negative and statistically significant at the 1% level. In fact, the results in columns (1) to (5) change little compared to those for the full sample. In columns (6) to (10), we focus on a balanced panel and select universities based on the number of AI professors in 2004. In particular, in columns (6) to (10), we select universities with at least one, two, three, four, and five AI professors in 2004, resulting in 74, 58, 42, 34, and 27 universities, respectively. The coefficients on *Tenure AI Brain Drain*$_{[t-6,t-4]}$ in columns (6) to (10) are all negative and statistically significant at the 1% level.

III. Economic Channels

In this section, we investigate potential channels for the negative effect of the AI brain drain on students' startups.

A. The Knowledge Transfer Channel

The knowledge transfer channel attributes the negative effect of AI faculty departures on startups to the reduced AI knowledge students receive from professors. This reduced knowledge can have several implications. For example, when professors teach new AI techniques, students can see how to apply a given technique to solve an existing problem. Other students may already have an idea for a startup, but they need to learn from professors the skills necessary to implement their idea. Students may also obtain knowledge from professors that will help them in talent acquisition, as they will be able to better distinguish applicants who are truly knowledgeable in AI. While we do not directly observe the type of knowledge that students receive from AI professors, we can assess the relevance of the knowledge transfer channel indirectly.

First, we find that the negative effect concentrated in departures that take place prior to students' enrollment (Table IV, column (3)). This means that when students have less overlap with a departed professor, they are less likely to establish an AI startup. Furthermore, if these students do establish a startup, they raise less funding when they have little overlap with departing professors (Table V, column (3)). The negative effect is smaller for both the extensive and the intensive margins if professors depart during students' enrollment at the university, presumably because these professors are able to transfer some AI knowledge to the students. We also find that the negative effect of the AI brain drain is significant only for tenured professors' departures (Table IV, column (4)). Tenured professors are more likely to supervise students, and they have more resources/larger labs. Assistant professors could also leave universities involuntarily because they are denied tenure, in which case the knowledge transfer disruption is probably smaller than it would be after the departure of an associate or a full professor.

To further investigate this channel, in Table VI, column (1), we decompose *AI Brain Drain*$_{[t-6,t-1]}$ into two categories of AI professors depending on whether the departing professor does research in deep learning. In column (1), we see that the negative effect of the AI brain drain on all AI entrepreneurs concentrate in the deep-learning professors. This result is consistent with the knowledge transfer channel because deep learning is a new machine-learning technique that requires a high level of expertise. Another way to see that departures of professors with the most cutting-edge knowledge are the most significant is to interact the AI brain-drain measure with an indicator of whether the university is ranked top-10 in CS. The interaction term in column (2) is negative and statistically significant at the 1% level, indicating that top-10 universities are most affected by tenured faculty departures.

In columns (3) to (8), we use the same two specifications for three subsamples of students: undergraduate, master's, and PhD. Together these three subsamples represent 86% of all AI entrepreneurs: 26% of the sample comprises undergraduates, 34% master's students, and 26% PhD students. We conjecture that PhD students and master's students are more affected by AI faculty departures than are undergraduate students, who are taking lower-level classes.

Table VI

Knowledge Transfer Channel

This table studies the effects of the AI brain drain on subsamples of entrepreneurs based on their highest degree. The dependent variable in columns (1) and (2) is the natural log of one plus the number of AI entrepreneurs. The dependent variable in columns (3) and (4) is the natural log of one plus the number of AI entrepreneurs whose highest degrees are bachelor's degrees. The dependent variable in columns (5) and (6) is the natural log of one plus the number of AI entrepreneurs whose highest degrees are master's degrees. The dependent variable in columns (7) and (8) is the natural log of one plus the number of AI entrepreneurs whose highest degrees are PhDs. Other variables are defined in the Appendix. All dependent and independent variables are winsorized at the 1st and 99th percentiles. For all specifications, robust standard errors are clustered at the university city level and are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	All Graduates		Undergraduate		Master		PhD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-Deep-Learning Brain Drain$_{[t-6,t-1]}$	−1.462		−0.678		−0.991		−0.554	
	(1.048)		(0.659)		(0.628)		(0.773)	
Deep-Learning Brain Drain$_{[t-6,t-1]}$	−9.066**		−2.541		−6.016**		−5.771***	
	(3.492)		(1.984)		(2.471)		(1.919)	
Untenured AI Brain Drain$_{[t-6,t-1]}$		−2.204		−0.030		−0.897		−0.904
		(2.629)		(1.530)		(1.280)		(1.145)
Tenured AI Brain Drain$_{[t-6,t-1]}$		−0.652		−0.337		−0.515		−0.408
		(1.054)		(0.688)		(0.894)		(0.661)
Tenured AI Brain Drain$_{[t-6,t-1]}$ ×*Top10*		−10.569***		−4.562		−6.875**		−6.870**
		(3.195)		(2.951)		(2.769)		(3.387)
Top10		0.334**		−0.082		0.394***		0.230**
		(0.148)		(0.089)		(0.146)		(0.092)
Rank control	Y	Y	Y	Y	Y	Y	Y	Y
Graduation year FE	Y	Y	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y	Y
N	756	756	756	756	756	756	756	756
Adj. R^2	0.574	0.581	0.200	0.207	0.399	0.419	0.324	0.337

Consistent with our conjecture, the coefficients on the AI brain drain of deep-learning professors (*Deep-Learning Brain Drain*$_{[t-6,t-1]}$) and on tenured professors from top-10 universities (*Tenured AI Brain Drain*$_{[t-6,t-1]} \times$ Top10) are negative and significant for master's and PhD entrepreneurs at the 5% significance level. The coefficients are negative but insignificant for entrepreneurs who hold only a bachelor's degree.

Moreover, for the undergraduate subsample, the coefficients on *Deep-Learning Brain Drain*$_{[t-6,t-1]}$ in column (3) and on the interaction term *Tenured AI Brain Drain*$_{[t-6,t-1]} \times$ *Top10* in column (4) are significantly smaller than the corresponding coefficients for the full sample at the 5% significance level. When we compare the coefficients on the same two variables for the master's or the PhD subsample to those of the full sample, the differences are all insignificant. Overall, Table VI presents additional evidence that is consistent with the knowledge transfer channel.

B. Alternative Explanations

In this section, we consider several alternative explanations for the negative effect of the AI brain drain on AI startups.

B.1. Following Professors

It is plausible that professors hire their students to work in their research groups in industry or their startups, in this case students do not establish AI startups. This channel should work more strongly for more recent departures, but we find that the results are stronger for faculty departures four to six years prior to students' graduation than for departures during students' enrollment in the program. Departing professors may hire more students from their former institutions several years after their departure because they get promoted to higher management roles or their startups receive external funding.

For professors who leave academia to join companies, the promotion effect should be less pronounced for top AI professors, like Yann LeCun and Geoffrey Hinton, who are hired to establish and manage AI groups in top companies like Facebook and Google. In Table VI, column (2), we show that the AI brain drain of tenured professors from universities with top-10 CS departments has a significantly stronger effect on AI startups than that for non-top-10 departments.

For professors who establish startups, we examine the relationship between funding raised by professors' startups and future students' AI startup formation. If the funding was used to hire students, we would expect the more funding that professors raise in the years closer to the students' graduation years, the more students will be hired and the fewer startups will be established by students. We compute the amount of funding raised by their startups during years $[t-6, t-4]$ and $[t-3, t-1]$ relative to students' graduation year t. In Table VII, we find that neither funds raised during $[t-3, t-1]$ nor funds raised during $[t-6, t-4]$ reduce the number of students' startups after

Table VII

Professors' Startup Funding and Students' Startup Formation

This table presents *Professor-Startup Funding Raised*$_{[t-3,t-1]}$ is the total funding amount received during $[t-3, t-1]$ by startups established by professors who left a given university. The dependent variable *AI Entrepreneur*, for the OLS model in columns (1) to (5), is the natural log of one plus the number of AI entrepreneurs who graduated in year t from a given university. Other variables are defined in the Appendix. All dependent and independent variables are winsorized at the 1st and 99th percentiles. For all specifications, robust standard errors are clustered at the university city level and are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	AI Entrepreneur				
	(1)	(2)	(3)	(4)	(5)
Professor-Startup Funding Raised$_{[t-3,t-1]}$	−0.006	−0.006	−0.006	−0.006	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Professor-Startup Funding Raised$_{[t-6,t-4]}$	−0.017	−0.016	−0.016	−0.016	−0.016
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
AI Brain Drain$_{[t-6,t-1]}$		−2.130**			
		(0.958)			
AI Brain Drain$_{[t-3,t-1]}$			−1.018*		
			(0.537)		
AI Brain Drain$_{[t-6,t-4]}$			−1.751**		
			(0.816)		
Untenured AI Brain Drain$_{[t-6,t-1]}$				−1.562	
				(3.172)	
Tenured AI Brain Drain$_{[t-6,t-1]}$				−2.428*	
				(1.244)	
Untenured AI Brain Drain$_{[t-3,t-1]}$					−2.769
					(2.173)
Untenured AI Brain Drain$_{[t-6,t-4]}$					0.310
					(1.853)
Tenured AI Brain Drain$_{[t-3,t-1]}$					−0.756
					(0.564)
Tenured AI Brain Drain$_{[t-6,t-4]}$					−3.684***
					(1.042)
Rank control	Y	Y	Y	Y	Y
Graduation year FE	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y
N	756	756	756	756	756
Adj. R^2	0.569	0.571	0.571	0.571	0.575

graduation. That is, the negative effects of the AI brain-drain measures are unaffected by the measures of professors' startup funding. It is, therefore, unlikely that the reduction in students' AI startups is caused by professors hiring away the best students to their startups.

B.2. The School Selection

When the AI brain drain takes place prior to students' enrollment, it can have a positive, neutral, or negative effect on students' desire to enroll in the affected university. A positive effect could exist if students interested in industry or startup jobs in AI prefer to enroll in a university with a high AI brain drain because they expect to leverage the university's industry ties to find a job. Alternatively, students may not respond to AI brain drain because they do not know about it, especially if professors maintain their academic affiliations. These two possibilities cannot explain our findings of the negative effect of AI brain drain on startups. The only explanation consistent with our results is that student quality is reduced as high-quality candidates decide to enroll in another university. In this case, the reduction in AI startups is explained by a reduction in the quality of incoming students and not by a reduction in the quality of AI education that students receive at the affected universities. We collect data about PhD scholarships in the area of AI to further investigate this possibility.

If AI faculty departures affect universities' ability to attract talented students who would later become AI entrepreneurs, we should see a reduction in the quality of incoming students following AI brain drain. While it is generally difficult to obtain a precise measure of student quality in a given university-year, we hand-collect panel data on the number of AI fellowships for PhD students. PhD students are more likely to respond to AI brain drain than undergraduate or master's students because doctoral students interact with faculty the most and their careers are most significantly affected by successful knowledge transfer between faculty and students. If faculty departures negatively affect enrollment by high-quality students, we would expect to see a drop in the number of PhD fellowship recipients following faculty departures.

We identify 424 AI PhD recipients who received prestigious fellowships between 2010 and 2018. To minimize the impact of program training, we focus on recipients who received the fellowship within the first two years of their PhD program enrollment. The recipients are identified through 11 graduate fellowship programs. Some of these programs are sponsored by government agencies (e.g., Graduate Research Fellowship Program (GRFR) by the U.S. National Science Foundation and NASA Space Technology Graduate Research Opportunities (NSTGRO) by the U.S. National Aeronautics and Space Administration), some are established by nonprofit organizations (e.g., Siebel Scholars Program by the Thomas and Stacey Siebel Foundation), and the rest are sponsored by tech companies such as Google, Facebook, NVIDIA, and Qualcomm.

We select these 11 programs using the following procedure. We start with the 45 graduate fellowship programs provided by the CS department at CMU.[16] Of these programs, 21 disclose previous recipients' profiles, which we use identify recipients' fields and enrollment years. We exclude fellowship programs that have a short history (i.e., awards starting after 2015) and those that only available to only a few universities. Table IA.VIII of the Internet Appendix provides the final list of the 11 programs used in our analysis.

We next examine the relationship between the AI-brain-drain measures and the number of fellowship recipients enrolled in a PhD program in year t at a

[16] Detailed information is available at https://www.cs.cmu.edu/~gradfellowships/.

given university. We report the results in Table VIII. In columns (1) to (3), the dependent variable is the natural log of one plus the number of the AI PhD recipients who received fellowship in the same year as their enrollment year t. In columns (4) to (6), the dependent variable is the natural log of one plus the number of the AI PhD recipients who received fellowship no later than $t+1$. In columns (7) to (9), the dependent variable is the natural log of one plus the number of the AI PhD recipients who received fellowship no later than $t+2$. For all nine specifications, the coefficients on *AI Brain Drain*$_{t-1}$, *Tenured AI Brain Drain*$_{t-1}$, *Untenured Brain Drain*$_{t-1}$, *Tenured AI Brain Drain*$_{[t-3,t-1]}$, and *Untenured AI Brain Drain*$_{[t-3,t-1}$ are all statistically insignificant. These results suggest that AI faculty departures in the past one year or during the past three years are unlikely to hinder universities' ability to attract high-quality PhD students.

B.3. Other Alternative Explanations

Professors can contribute to student success beyond transferring knowledge. For example, professors could introduce students to VCs, in this case the AI brain drain can reduce students' funding opportunities. This channel should be stronger for VCs located in the same city as the university because professors are more likely to know local VCs. However, nonlocal entrepreneurs are more negatively affected by AI brain drain (see Table IA.II in the Internet Appendix) than local entrepreneurs, and thus we conclude that this channel is unlikely to drive our benchmark results.

Another possibility is that professors who leave for industry or establish their own startups have better general skills, such as leadership skills. Therefore, instead of AI-specific knowledge, students may simply learn managerial skills from the departing professors. This alternative explanation cannot shed light on the negative effect of the AI brain drain is driven by the departures of deep-learning professors (Table VI, column (1)). It is not clear why leadership skills or other general skills would be more pronounced for professors who work on deep neural networks than for professors who work on another type of machine learning algorithms.

Last, we consider whether high demand for AI talent can jointly explain the AI brain drain and the increase in students with AI knowledge joining corporations and establishing fewer startups. This explanation requires that the demand for AI talent is university-specific, otherwise cannot explain our cross-sectional university-level findings, and is time-varying, as we have university-level fixed effects to absorb factors that are not time-varying. Moreover, this university-level, time-varying demand factor should affect the students with a significant delay relative to the professors (at least four- to six-year lag). One possibility is that the AI brain-drain signals to recruiters where they should be looking for AI talent. We are less confident in this explanation because informational frictions are unlikely to cause a four- to six-year delay in demand shocks. Also, they are more likely to affect lower-ranked universities where recruiters are not likely to search for AI talent otherwise. However, our

Table VIII

School Selection Channel

In this table, we test the relationship between the AI brain drain and the quality of incoming AI PhD students, measured by the number of AI PhD students who received a fellowship from one of 11 prestigious fellowship programs. Details of these fellowship programs are described in Table IA.VIII of the Internet Appendix. In columns (1) to (3), the dependent variable is the natural log of one plus the number of PhD students who received a fellowship in their enrollment year t. In columns (4) to (6), the dependent variable is the natural log of one plus the number of PhD students who received a fellowship no later than $t+1$. In columns (8) to (9), the dependent variable is the natural log of one plus the number of PhD students who received a fellowship no later than $t+2$. Other variables are defined in the Appendix. All dependent and independent variables are winsorized at the 1st and 99th percentiles. For all specifications, robust standard errors are clustered at the university city level and are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Awarded in Enrollment Year			One Year within Enroll.			Two Years within Enroll.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI Brain Drain$_{t-1}$	0.139			−0.128			−0.118		
	(0.187)			(0.214)			(0.333)		
Untenured AI Brain Drain$_{t-1}$		0.596			0.103			0.597	
		(0.466)			(0.448)			(0.738)	
Tenured AI Brain Drain$_{t-1}$		0.076			−0.171			−0.261	
		(0.221)			(0.257)			(0.441)	
Untenured AI Brain Drain$_{[t-3,t-1]}$			0.045			−1.230			0.647
			(0.574)			(0.928)			(1.679)
Tenured AI Brain Drain$_{[t-3,t-1]}$			0.235			0.117			1.229
			(0.215)			(0.312)			(0.745)
Rank control	Y	Y	Y	Y	Y	Y	Y	Y	Y
Enrollment year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	756	756	756	756	756	756	756	756	756
Adj. R^2	0.357	0.359	0.356	0.428	0.428	0.429	0.613	0.613	0.616

results indicate that the AI brain drain is stronger for universities with top-10 CS departments. These universities are already known to produce AI talent, and experiencing an AI brain drain is more likely to signal a reduction in the quality of the AI knowledge that students receive.

IV. Conclusion

In this paper, we hand-collect data about the AI brain drain from North American universities to industry. Between 2004 and 2018, 211 AI professors left academia either partially or fully to establish their own startups or to join other firms. The resulting AI brain drain from academia intensified toward the end of the sample period. In 2018, 21 universities lost 40 AI faculty whose citations accounted for, on average, 19% of all the citations received by all AI professors at their universities.

We document a negative relationship between the AI brain drain and the number of AI startups established by students at North American universities. Moreover, students' AI startups raised less funding many years after their universities experienced AI brain drain. While we cannot randomly pull professors from academia to industry, a number of findings support a causal interpretation of the results. First, professors leave academia largely because of significantly larger compensation, unmatched data, and computational resources available in the industry. Second, we see the effect only on AI startups (i.e., no effect on non-AI startups) formed by students at the same university. Third, we find that time-varying city-level shocks are unlikely to jointly explain faculty departures and students' entrepreneurial activity. Fourth, we show that the effect holds only for AI startups and only for tenured professors who did not overlap with students, professors from top schools, and deep-learning professors. Last, a significant time gap exists between an AI professor's departure and students' startup formation and funding decision, which contributes to the causal interpretation of the results.

Because AI startups drive innovation and growth, it is important to understand the reasons behind the reduction in the number of startups and their funding, which occur years after AI professors leave academia. Our findings are consistent with the knowledge transfer channel. The AI brain drain effectively restricts AI knowledge from being transferred from professors to future founders. If entrepreneurs can raise funding and hire employees with deep AI knowledge, the AI brain drain should not affect the number of AI startups formed by students of the affected universities. Our finding that the AI brain drain is followed by a significant reduction in both the number of AI startups and their funding suggests that founders' academic knowledge of AI is important for startups' success. We also show that AI startups are more likely than non-AI startups to have at least one co-founder with a PhD degree. We further find that a positive monotonic relationship exists between founders' formal education and the amount of funding they receive. This suggests that academic knowledge of AI is an important factor in successful fundraising.

Students can gain different types of knowledge from professors, but we find that the brain drain of deep-learning professors has the most significant negative effect on startups. This rules out the possibility that the effect of the AI brain drain on startups operates via a reduction in students' general knowledge of programming, project management, or leadership skills. The negative effect of the brain drain of deep learning professors is significant for master's students and PhD students but not for undergraduate students, further confirming that the advanced knowledge transfer is what matters for founders' success. Another piece of evidence in support of the knowledge transfer channel is that the negative effect of the AI brain drain of tenured professors is more significant for universities with top CS departments. Presumably, AI professors in these departments are more likely to conduct cutting-edge research in AI. Moreover, this result is significant only for startups founded by entrepreneurs with a master's or a PhD degree.

Of all the AI professors who leave academia, a subgroup of 62 professors is most likely to transfer knowledge that is helpful to startup formation and funding. These professor-entrepreneurs left academia partially or fully to establish their own startups. We construct a new measure of professors' knowledge applicability based on the amount of funding that their startups raise from the time of the departure through 2020. We find that the more applicable the departing professors' knowledge is, the fewer AI startups are later founded by students. Our AI brain-drain measures, especially for deep-learning professors, remain negative and statistically significant, even after controlling for the amount of funding that the professors' startups receive. We also show that when professors' startups raise funds prior to students' graduation, there is no significant reduction in the number of students who become AI entrepreneurs. This result suggests that the negative effect of AI brain drain on startup formation and funding is unlikely to be due to professor-entrepreneurs hiring the best students for their startups.

We consider several alternative explanations for our main results. First, we can plausible rule out the possibility that university- or city-level shocks drive our results. Second, we show that it is unlikely that good students avoid universities with high AI brain drain because newly enrolled PhD students at universities with AI brain drain are not less likely to receive a prestigious fellowship within one year of their enrollment. Third, our findings are less consistent with the possibility that departing professors hire the best students and, as a result, reduce the available human capital for startup formation. Fourth, we show that it is unlikely that some unobserved talent-demand factors induce professors to leave universities and, at the same time, channel the best students to work for companies. Last, we argue that it is unlikely that professors connect students with VCs because such introductions are more likely to benefit local entrepreneurs, while we find that the affected startups are not located in the same city as the university.

When professors suddenly become in high demand outside of academia, both fundamental research and knowledge dissemination in their universities are negatively affected. In this paper, we use the AI brain drain to shed light on the importance of highly specialized academic knowledge for entrepreneurs. We do not study the short-term economic benefits of the AI brain drain or its long-term welfare implications. We leave these important questions for future research.

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Appendix: Variable Definitions

Variable	Definition
AI Faculty$_{it}$	Number of AI faculty members in year t at university i.
AI Brain Drain$_{it}$	Number of tenure-track or tenured AI faculty departures in year t at university i, scaled by AI Faculty$_{i,t}$.
Tenured AI Brain Drain$_{it}$	Number of tenured AI faculty departures in year t at university i, scaled by AI Faculty$_{i,t}$.
Untenured AI Brain Drain$_{it}$	Number of untenured AI faculty departures in year t at university i, scaled by AI Faculty$_{it}$.
Deep-Learning Brain Drain$_{it}$	Number of deep-learning AI faculty departures in year t at university i, scaled by AI Faculty$_{it}$, where deep-learning faculty are identified by published papers that use deep neural networks, such as recurrent or convolutional neural networks, or develop new deep-learning techniques.
Non-Deep-Learning Brain Drain$_{it}$	Number of non-deep-learning AI faculty departures in year t at university i, scaled by AI Faculty$_{it}$.
AIBrainDrain$_{i[t-j,t-k]}$	The average of AI Brain Drain$_{it}$ during period $[t-j, t-k]$, $(\sum_{n=j}^{n=k} \text{AI Brain Drain}_{i,t-n})/(j-k+1)$.
Rank$_{it}$	A continuous measure for a CS department ranking in year t at university i, based on the department's presence in the most prestigious publication venues provided by CSRanking.org.
Top 10$_{it}$	A dummy variable equal to one if a North American university i with Rank$_{it}$ ranked in the top 10 in year t.
AI Entrepreneur$_{it}$	Number of AI entrepreneurs who graduate in year t from university i and establish AI startups after graduation.
Non-AI Entrepreneur$_{it}$	Number of entrepreneurs who graduate in year t from university i and establish IT startups (excluding AI) after graduation.
Early-stage financing	Total funding received in preseed, seed, and Series-A round in million dollars.
Preseed-round financing	Preseed-round funding amount in million dollars.
Seed-round financing	Seed-round funding amount in million dollars.
Series-A financing	Series-A-round funding amount in million dollars.
Professor-Startup Funding Raised$_{i[t-i,t-j]}$	Total amount of financing in million dollars received during $[t-i, t-j]$ by startups established by professors who left university i, where t is the student graduation year.

REFERENCES

Acemoglu, Daron, and Pascual Restrepo, 2018, Artificial intelligence, automation, and work, in The Economics of Artificial Intelligence: An Agenda, pp. 197–236 (University of Chicago Press, Chicago, IL).

Aghion, Philippe, Benjamin Jones, and Charles Jones, 2018, Artificial intelligence and economic growth, in The Economics of Artificial Intelligence: An Agenda, pp. 237–282 (University of Chicago Press, Chicago, IL).

Aubry, Mathieu, Roman Kräussl, Gustavo Manso, and Christophe Spaenjers, 2019, Machine learning, human experts, and the valuation of real assets, CFS Working paper series.

Azoulay, Pierre, Benjamin Jones, Daniel Kim, and Javier Miranda, 2020, Age and high-growth entrepreneurship, *American Economic Review: Insights* 2, 65–82.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson, 2023, Artificial intelligence, firm growth, and product innovation, Working paper.

Babina, Tania, Alex He, Sabrina Howell, Elisabeth Ruth Perlman, and Joseph Staudt, 2020, The color of money: Federal vs. industry funding of university research, Working paper.

Babina, Tania, and Sabrina Howell, 2020, Entrepreneurial spillovers from corporate R&D, Working paper.

Bernstein, Shai, Emanuele Colonnelli, Davide Malacrino, and Tim McQuade, 2022, Who creates new firms when local opportunities arise? *Journal of Financial Economics* 143, 107–130.

Bernstein, Shai, Arthur Korteweg, and Kevin Laws, 2017, Attracting early-stage investors: Evidence from a randomized field experiment, *Journal of Finance* 72, 509–538.

Bessen, James, Stephen Michael Impink, Lydia Reichensperger, and Robert Seamans, 2022, The role of data for AI startup growth, *Research Policy* 51, 104513.

Chen, Luyang, Markus Pelger, and Jason Zhu, 2019, Deep learning in asset pricing, Working paper.

Cockburn, Iain, Rebecca Henderson, and Scott Stern, 2018, The impact of artificial intelligence on innovation, NBER Working paper.

Corradin, Stefano, and Alexander Popov, 2015, House prices, home equity borrowing, and entrepreneurship, *Review of Financial Studies* 28, 2399–2428.

Dalle, Jean-Michel, Matthijs Den Besten, and Carlo Menon, 2017, Using crunchbase for economic and managerial research, OECD.

Economist, 2016, Million-dollar babies: As silicon valley fights for talent, universities struggle to hold on to their stars, *Economist*, April 2.

Elfenbein, Daniel, Barton Hamilton, and Todd Zenger, 2010, The small firm effect and the entrepreneurial spawning of scientists and engineers, *Management Science* 56, 659–681.

Erel, Isil, Léa Stern, Chenhao Tan, and Michael Weisbach, 2021, Selecting directors using machine learning, *Review of Financial Studies* 34, 3226–3264.

Ersahin, Nuri, Rustom Irani, and Katherine Waldock, 2021, Can strong creditors inhibit entrepreneurial activity? *Review of Financial Studies* 34, 1661–1698.

Etzioni, Oren, 2019, AI academy under siege, Inside Higher ED.

Ewens, Michael, and Matt Marx, 2018, Founder replacement and startup performance, *Review of Financial Studies* 31, 1532–1565.

Gompers, Paul, Josh Lerner, and David Scharfstein, 2005, Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999, *Journal of Finance* 60, 577–614.

Grennan, Jillian, and Roni Michaely, 2020, Artificial intelligence and high-skilled work: Evidence from analysts, Swiss Finance Institute Research Paper.

Gu, Shihao, Bryan Kelly, and Dacheng Xiu, 2020, Empirical asset pricing via machine learning, *Review of Financial Studies* 33, 2223–2273.

Guerreiro, Joao, Sergio Rebelo, and Pedro Teles, 2022, Should robots be taxed? *Review of Economic Studies* 89, 279–311.

Hall, Bronwyn, and Josh Lerner, 2010, The financing of R&D and innovation, in Handbook of the Economics of Innovation, Vol. 1. pp. 609–639, (Amsterdam: North-Holland).

Heaton, James, Nick Polson, and Jan Hendrik Witte, 2017, Deep learning for finance: Deep portfolios, *Applied Stochastic Models in Business and Industry* 33, 3–12.

Hvide, Hans, and Benjamin Jones, 2018, University innovation and the professor's privilege, *American Economic Review* 108, 1860–1898.

Jin, Zhao, 2020, How do large firms affect entrepreneurial entry: Evidence from Amazon's HQ2 search, Working paper.

Kamepalli, Sai Krishna, Raghuram Rajan, and Luigi Zingales, 2020, Kill zone, Working paper.

Kaplan, Steven N., Berk Sensoy, and Per Strömberg, 2009, Should investors bet on the jockey or the horse? Evidence from the evolution of firms from early business plans to public companies, *Journal of Finance* 64, 75–115.

Kaplan, Steven N., and Per Strömberg, 2003, Financial contracting theory meets the real world: An empirical analysis of venture capital contracts, *Review of Economic Studies* 70, 281–315.

Kerr, William, Josh Lerner, and Antoinette Schoar, 2011, The consequences of entrepreneurial finance: Evidence from angel financings, *Review of Financial Studies* 27, 20–55.

King, Robert, and Ross Levine, 1993, Finance and growth: Schumpeter might be right, *Quarterly Journal of Economics* 108, 717–737.

Korinek, Anton, and Joseph Stiglitz, 2017, Artificial intelligence and its implications for income distribution and unemployment, NBER Working paper.

Kwok, Viem, and Hayne Leland, 1982, An economic model of the brain drain, *American Economic Review* 72, 91–100.

Lazear, Edward, 2004, Balanced skills and entrepreneurship, *American Economic Review* 94, 208–211.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton, 2015, Deep learning, *Nature* 521, 436–444.

Lerner, Josh, and Ulrike Malmendier, 2013, With a little help from my (random) friends: Success and failure in post-business school entrepreneurship, *Review of Financial Studies* 26, 2411–2452.

Metz, Cade, 2017, Tech giants are paying huge salaries for scarce A.I. talent, *New York Times*, October 22.

Metz, Cade, 2018, A.I. researchers are making more than $1 million, even at a nonprofit, *New York Times*, April 19.

Nagel, Stefan, 2021, Machine Learning in Asset Pricing (Princeton University Press, Princeton, NJ).

Nanda, Ramana, and Jesper Sørensen, 2010, Workplace peers and entrepreneurship, *Management Science* 56, 1116–1126.

Procaccia, Ariel, 2019, Tech giants, gorging on AI professors is bad for you, *Bloomberg*, January 7.

Roche, Maria, Annamaria Conti, and Frank Rothaermel, 2020, Different founders, different venture outcomes: A comparative analysis of academic and non-academic startups, *Research Policy* 49, 104062.

Romer, Paul M., 1990, Endogenous technological change, *Journal of Political Economy* 98, S71–S102.

Sample, Ian, 2017, We can't compete: Why universities are losing their best AI scientists, *Guardian*.

Schumpeter, Joseph, 1942, Creative destruction, *Capitalism, Socialism and Democracy* 825, 82–85.

Trajtenberg, Manuel, 2018, AI as the next GPT: A political-economy perspective, NBER Working paper.

Zhang, Daniel, Nestor Maslej, Erik Brynjolfsson, John Etchemendy, Terah Lyons, James Manyika, Helen Ngo, Juan Carlos Niebles, Michael Sellitto, Ellie Sakhaee, Yoav Shoham, Jack Clark, and Raymond Perrault, 2022, The AI index 2022 annual report, Stanford University.

Zucker, Lynne, Michael Darby, and Marilynn Brewer, 1998, Intellectual human capital and the birth of US biotechnology enterprises, *American Economic Review* 88, 290–306.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.