Venture Capital Response to Government-Funded Basic Science*

Roham Rezaei†, and Yufeng Yao‡

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Abstract

Science-based R&D can deter venture capitalists due to high technical uncertainty. We study whether mission-oriented public funding, which supplies basic science as a public good, fosters VC investments. Our quasi-natural experiment is the BRAIN Initiative (BI), a government-funded program with the goal of mapping the human brain. Using a large language model, we first show the large spillover effects of BI in neurotech. In a difference-in-differences analysis, we find an increase in VC investments in neurotech startups accompanied by higher valuations and more successful VC exits following the BI. The channels driving these results suggest reduced technical uncertainty: 1) increased supply of high-skilled academic labor; 2) more innovation, including breakthrough patents; 3) enhanced integration with complementary technologies, especially AI and big data, which aligns with the BI's data-driven mission. Our results suggest the supply of government-backed science and scientists can spur follow-on private investments in emerging technologies.

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†UNSW Business School, University of New South Wales. Email: r.rezaei@unsw.edu.au
‡UNSW Business School, University of New South Wales. Email: yufeng.yao1@unsw.edu.au

1. Introduction

Technical innovation necessitates investment in the underlying basic science. Seminal works such as Nelson (1959) and Arrow (1962) argue that private markets may lack incentives for investment in basic science: *"because it is risky, because the product can be appropriated only to a limited extent, and because of increasing returns in use."* The scientific process is characterized by asymmetric information, long timelines, and thus high uncertainty. The inability to appropriate returns and increasing returns in use stem from the non-excludable nature of scientific knowledge. Basic science generates spillovers that benefit society at large but cannot be fully captured by the original investor.[1] These features impair the decentralized market's coordination through the price mechanism.[2] Thus, Nelson (1959) and Arrow (1962) propose that the government should bridge the funding gap in basic science. The resulting knowledge and human capital are supplied as *public goods* for the market to commercialize.

Venture capital (VC) investments seem to reflect these ideas. Although VC is a major market mechanism in financing innovation (Howell, Lerner, Nanda, and Townsend, 2020), there are concerns about the increasing focus of VC funds on the IT sector to the detriment of nascent technologies built on new science. These technologies are crucial for addressing significant societal challenges, such as climate change and Alzheimer's disease. Consequently, underinvestment in them leads to substantial welfare loss.[3] Lerner and Nanda (2020) argue that the typical VC model—characterized by small funds with a finite life of 10-12 years—has limitations in addressing the technical uncertainty in new science. Commercializing emerging science requires longer timelines and often high upfront R&D costs, not amenable to how VCs address the Knightian uncertainty—i.e., unknown variance—of the entrepreneurial process.[4] Kerr, Nanda, and Rhodes-Kropf (2014) argue that VCs finance startups in stages, with each stage serving as an experiment that reveals information about the project's viability and reduces uncertainty. The IT sector aligns with the VC criteria because technological advances such as cloud computing have lowered the cost of early-stage experimentation in software (Ewens, Nanda, and Rhodes-Kropf, 2018). In contrast, reducing uncertainty in new sciences requires large-scale investment beyond the scale of most VC funds. Such uncertainty also deters potential

[1] The difficulty arises from the unpatentable, sequential and cumulative nature of science—that is, each successive invention builds on the preceding one.

[2] See e.g., Scotchmer (1991); Bresnahan and Trajtenberg (1995); Green and Scotchmer (1995)

[3] Figure 1 shows an increase in the proportion of startups classified as software compared to a decline in startups holding patents before their first VC financing.

[4] Knight (1921) argues that the entrepreneur faces uncertainty, fundamentally different from risk. Under risk, success probabilities and expected values are known, but under uncertainty they are unknown.

entrepreneurs—typically academic scientists with secure, salaried positions—from entering entrepreneurship due to the high opportunity costs (Hall and Woodward, 2010). Kerr et al. (2014) thus suggest that institutions such as government and academia are essential in enabling experimentation in new science.

Interestingly, the early stage of the IT sector, the realm of venture capital, highlights the role of government in reducing technical uncertainty. The internet and many related VC-backed technologies, such as Cisco's routers and Google's search algorithms, all originated from Pentagon-funded research (Lerner, 2012). Mallaby (2022) discusses the development of web browsers as another example. Mosaic, one of the earliest web browsers, was instrumental in popularizing the internet by integrating multimedia such as text and graphics (Britannica, 2020). Marc Andreessen developed Mosaic at the National Center for Supercomputing Applications, an NSF-funded lab at the University of Illinois at Urbana–Champaign in late 1992. The funding was legislated under the High-Performance Computing Act of 1991. After the popularity of Mosaic, the university offered Andreessen a permanent contract on the condition of leaving the management of Mosaic to NSF. Andreessen responded by quitting his university job and founding Mosaic Communications to work on building a rival product. With the backing of VC firm Kleiner Perkins, Mosaic Communications developed the Netscape Navigator. In 1999, Netscape was acquired by AOL for $4.3 billion.[5] Andreessen later remarked that *"if it had been left to private industry, it wouldn't have happened ... at least, not until years later."*[6]

Nonetheless, the effect of public funding for basic science on the investment behavior of venture capitalists (VCs) is far from clear. Public funding mechanisms vary significantly, and their efficacy depends crucially on their design (Howell, 2017, 2024). Public funds may be allocated to projects with limited technological applications (e.g., cosmology or fusion energy). They may also be driven by the political agendas of the government bureaucrats (Lerner, 2009). Furthermore, public funding could potentially crowd out private investment by subsidizing entrepreneurial R&D, thereby reducing the need for dilutive VC financing. Conversely, anecdotal evidence suggests that large-scale, coordinated science programs can successfully crowd in private investment (Mazzucato, 2021).[7] These programs, also known as "moonshot",[8] are becoming increasingly popular worldwide. In this paper, we study whether and how mission-oriented government

[5] Marc Andreessen later founded Andreessen-Horowitz, one of the top VC firms globally.

[6] Perine (2000)

[7] The innovation literature underscores the role of such programs in catalyzing technology and industry incubation (Arora, Belenzon, Patacconi, and Suh, 2020; Agarwal, Kim, and Moeen, 2021; Gross and Roche, 2023; Gross and Sampat, 2023). Several pivotal technologies, such as nuclear energy, antibiotics, satellite navigation, mRNA vaccines, and microwave radar, can be traced back to such focused public investments.

[8] Inspired by NASA's Apollo program to land a man on the moon.

programs foster VC investments.

Studying this question requires a mission-oriented program orthogonal to the scientific advances or market dynamics. We believe that the BRAIN Initiative possesses such features. Brain Research Through Advancing Innovative Neurotechnologies (BRAIN) is a government program aimed at revolutionizing our understanding of the human brain. In 2013, President Obama designated brain research as a *Grand Challenge*, a term used for mission-oriented programs for expanding foundational knowledge. Another example of a *Grand Challenge* is the Human Genome Project (HGP), which aimed to sequence DNA bases in the human genome. The HGP spurred the emergence of the market for genetic therapy. Battelle Institute (2011) estimates that for every federal dollar invested in the HGP, $141 was generated in the economy. The HGP served as a role model for the BRAIN Initiative (BI), and its success has significantly influenced BI's design.

Similar to HGP, BI has a mission: mapping the human brain. This mission, proposed by the leading neuroscientists through two influential papers,[9] seeks to advance understanding of macro-level neural circuit activity. This foundational knowledge has implications not only for neurological disorder treatment (e.g., Alzheimer's, Parkinson's, epilepsy) but also directly contributes to wider technological areas—e.g., medical devices, prosthetics with sensory feedback, brain-computer interfaces, and cognitive computing (The White House, 2013; NIH, 2014a). Six government agencies supported the BI,[10] showing its wide contributions. However, the National Institute of Health (NIH) was the leading agency that coordinated the program. We estimate that the US government has spent over $5B in funding BI between 2014 and 2022 and the program is set to run until 2026.

A potential endogeneity concern is that the inherent promise of neurotechnologies might have attracted VC investment independent of the BI. However, several factors mitigate this concern. First, the scale of the BI, with over $5 billion in government funding, dwarfs the typical investment capacity of individual VC funds, which average $145 million per fund.[11] Second, VC funds are unlikely to *coordinate* investments to produce a non-excludable good like a comprehensive brain map. Third, leading up to the BI, even pharmaceutical companies, traditionally major investors in neuroscience R&D, were cutting their expenditures in the field due to high uncertainty and failure rates.[12] While it remains possible that unobservable advances in neuroscience could have coincided with

[9]See (Alivisatos, Chun, Church, Greenspan, Roukes, and Yuste, 2012; Alivisatos, Chun, Church, Deisseroth, Donoghue, Greenspan, McEuen, Roukes, Sejnowski, Weiss, and Yuste, 2013)

[10]NSF (science), FDA (food and drugs), IARPA (intelligence), DARPA (defence), and DoE (energy)

[11]This is based on all PitchBook's US VC funds.

[12]See for example: (Miller, 2010; Nutt, 2011; Insel and Landis, 2013; Choi, Armitage, Brady, Coetzee, Fisher, Hyman, Pande, Paul, Potter, Roin, and Sherer, 2014)

the BI, our dynamic estimations show no evidence of a pre-trend or elevated VC activity in the neurotechnology space prior to 2013. Furthermore, BI was designated as a *Grand Challenge* from a diverse menu of 12 other scientific projects (Sejnowski, 2014), highlighting a degree of randomness. This mitigates the concern that the markets broadly anticipated the shock.

For BI to be a relevant shock, it must be effective in producing influential science with high commercial potential. We use three separate measures of commercial viability to validate that BI is a relevant shock. Marx and Fuegi (2020, 2022) provide data on realized citations to academic articles in the patent text. Using this data, we find that BI-funded research is more likely to be cited in patents than similar publications from non-BI grants in neuroscience. We obtain similar results using data from Masclans, Hasan, and Cohen (2024), which predict the commercial potential of a publication—i.e., the ex-ante likelihood that an academic publication receives patent citations. Nonetheless, patent-to-publication citations likely underestimate the effect of BI due to its basic science nature. This aligns with Nelson and Arrow's argument that the outcomes of basic science R&D cannot be fully appropriated. Scientific discoveries, such as the fundamental principles of how the brain works, are not directly patentable. Also, patents tend to cite prior art immediately related to the invention, suggesting that the broader scientific foundation upon which an invention is based is less frequently cited.[13] Another issue arises from the truncation issue in patent citations. This is specifically relevant in our setting, given that the BI occurs in the second half of our sample.

Lerner and Seru (2021) suggest that machine learning models can overcome some of these limitations.[14] Inspired by the methodologies used in Masclans et al. (2024) and Giczy, Pairolero, and Toole (2022), we employ a Large Language Model (LLM) to identify patents influenced by BI research output. We fine-tune a SciBERT model[15] using a labeled dataset that includes positive cases—the titles and abstracts of research papers resulting from BI research outputs[16]—and negative cases, consisting of neuroscience publications before the BI. The model estimates that BI knowledge has influenced at least 66% of all neuroscience-related patents.

To study the economic impacts of BI, we construct a comprehensive dataset with information on startup financing, innovation, and employees. We compile a sample of

[13] For example, while the BI-funded Cell Census Network (BICCN) helps identify cells that stop functioning in Parkinson's disease, the statistical models that BICCN is based on may be too abstract for citation in Parkinson-related patents.

[14] A similar suggestion is echoed by USPTO's chief economist (Toole, Pairolero, Forman, and Giczy, 2020)

[15] BERT is a foundational model released by Google AI in 2018 (Devlin, Chang, Lee, and Toutanova, 2018). SciBERT is a version of BERT pre-trained on a large corpus of scientific text (1.14M scientific articles).

[16] The majority of patents citing BI research are associated with academic institutions.

US VC-backed startups receiving their first VC funding round between 2000-2019 using PitchBook and follow their outcomes until 2022. We link this to LinkedIn data to gain insights about the startup employees and their employment history. We specifically identify the academics who have founded or worked for these startups. We also find information on startup innovation activity by identifying patent portfolios of startups from USPTO's PatentsView, augmented with Founding Patents data of Ewens and Marx (2023). We identify a startup as a *Neuro startup* if it has at least one patent related to neuroscience based on textual analysis of the patent's technology classes.[17] To examine the direct impact of the BI, we collect data on grants, including the dollar amount, output publications, grant type, organizations involved, and principal investigators from the websites of funding agencies. Subsequently, we extract detailed information on the publications enabled by these grants, including publication years, citations, and co-authors, from Scopus.

We find that *Neuro startups* receive between 31% and 50% larger investments from the VCs post-BI compared to various startup control groups. Such investments are also made at valuations that are 23% to 41% higher. These results suggest that the BI made neurotechnology more *investable*[18] for VCs. If public funding reduces the technical uncertainty of *Neuro startups*, this effect is likely reflected when VCs invest in the company for the first time. In the first VC round, the uncertainty is skewed toward technological feasibility rather than product performance or market validation. We find our results to be consistent across the first rounds. The reduced technical uncertainty is also reflected in VCs' successful exits from their neuro investments through IPOs or acquisitions;[19] this demonstrates that the broader market also recognizes the value of these firms. We also find that VC's exit their neurotech investments faster, indicating shorter R&D timelines, enabled by the BI. Our control groups include all VC-backed startups, those with a patent,[20] financing rounds within five years before and after the shock and startups in the healthcare sector. We obtain consistent results across all these control groups.

We propose three non-mutually exclusive channels to explain the more favorable VC financing and outcomes for *Neuro startups*: 1) higher supply of skilled labor reflected in the presence of STEM academics either as early senior employees or inventors, 2) increased innovation, and 3) enhanced adaptability of neurotechnologies to other complementary technologies. The focus on human capital is motivated by Bernstein, Korteweg,

[17] Our results are robust when we identify *Neuro startups* by analyzing the startup's business descriptions.

[18] By *investable* and *investability*, we mean more attractive investment opportunities throughout the paper.

[19] Following Ewens and Rhodes-Kropf (2015), a successful acquisition is an exit value greater than twice capital invested.

[20] Given that these are only around 15% of VC-backed startups, we believe this represents a sample of more science-based startups.

and Laws (2017), who find that investors place primary emphasis on the startup's human capital when deciding on funding early-stage ventures. We focus on academics because BI funding was predominantly allocated to academic research. We find that *Neuro startups* are 10% more likely to have STEM academics in senior positions in the first three years after being founded, post-BI. In a panel of startup-year observations, we observe a higher likelihood of inventor-employees in *Neuro startups* coming from academic backgrounds after the BI. [21] Neuralink, a prominent *Neuro startup* founded in 2017, is an example of a startup that benefited from the human capital funded by the BI. Not only is Neuralink one of the top three employers of scientists who have published with the BI funding, but its founding team also includes one such scientist, Philip Sabes, a professor of neuroscience at UCSF.

Moreover, we note that *Neuro startups* file for more patents compared to other patenting startups, suggesting more successful R&D outcomes. While we do not find that the average patent of *Neuro startups* receives more citations, we do find evidence of more breakthrough patents by these firms. The larger number of patents, including breakthrough patents, represents a richer portfolio of tangible IP-based assets, which is attractive to VCs as it increases the prospects for strategic partnerships, acquisitions, or even IPOs (Caskurlu, 2019; Farre-Mensa, Hedge, and Ljungqvist, 2020; Bowen, Frésard, and Hoberg, 2023). Lastly, we use USPTO's AI Patent Dataset to identify inventions that have used AI in the innovation process. We find that post-BI *Neuro startups'* patents are twice as likely to employ AI-enabled patents compared to other patenting startups, in line with more integration of data science into neuroscience-related technologies.

This reallocation to a more interdisciplinary approach could be attributed to the goals of BI. The human brain comprises 86 billion neurons, forming over 100 trillion connections (Nature, 2021). To Decode this complex network, BI funded significant open-access datasets[22] and computational infrastructure for analyzing these gigantic datasets (Zador, Escola, Richards, et al., 2023). We find that NIH's BI grants are three times more likely to fund data science-related areas than conventional NIH neuroscience grants. Furthermore, BI emphasizes interdisciplinary research between neuroscientists, engineers, statisticians, chemists, and data scientists. A comparison of the underlying technological areas that neurotech companies are active in shows that after the BI, neurotech becomes broader than life sciences and encompasses areas such as AI and machine learning, big data, and

[21] These findings are consistent with those of Babina, He, Howell, Perlman, and Staudt (2023), who demonstrate that in the opposite scenario, i.e., for an academic facing a cut in her public funding, the rate of entrepreneurship drops.

[22] An editorial article in Nature (2021) notes that by the time BI ends *"it will have created a gold mine for clinical researchers working on psychiatric, neurodegenerative and neurodevelopmental disorders."*

brain-computer interfaces. This is also reflected in acquisition patterns in the neuro market. Post-BI, the number of acquisitions of *Neuro startups* sharply increases. Before the BI, acquirers were almost exclusively from the healthcare sector. However, after the BI, acquirers are from a diversified range of sectors, including IT, B2B, and B2C.

The potential synergy between neuroscience and AI raises an omitted variable bias concern. VCs might invest more in *Neuro startups* startups not due to the BI, but because neuroscience is fertile ground for AI applications. While our results are robust to the exclusion of startups explicitly employing AI and big data technologies, we further provide direct evidence on the treatment effects of BI. Following Arora, Belenzon, Cioaca, Sheer, and Zhang (2023), who highlight the role of university-trained labor in driving corporate innovation, we focus on researchers directly involved in BI-funded projects, as observed through publications funded by the BI. We collect data on these publications through queries from the NIH and NSF websites, which provide public data on grants and output publications. These publications are linked to Scopus to identify co-authors. The underlying assumption is that these scientists embody the knowledge and expertise generated by the BRAIN Initiative. For each *Neuro startup*, we identify the first financing round after hiring a BRAIN scientist, classifying this as the treatment point. We find that compared to non-treated neurotechnology startups, those employing BI scientists raise larger VC funding. This finding provides direct evidence that VCs value the skilled labor developed through the BI.

Contribution to the Literature

Our work contributes to a large body of literature studying the role of public funding in spurring private investments in entrepreneurship and innovation. Fleming, Greene, Li, Marx, and Yao (2019) show US corporations and startups increasingly rely on government-backed innovation. Bai, Bernstein, Dev, and Lerner (2021) propose that public-private co-investments are more effective when the rule of law is greater, and the government invests in earlier-stage projects. Lerner, Manley, Stein, and Williams (2024) highlight the role of place-specific factors–i.e., institution effects vis-à-vis researcher effects–in commercializing academic innovation.

Closely related are Lerner (1999) and Howell (2017), who study the real and financial impacts of government grants in the form of Small Business Innovation Research (SBIR) on startups. Lerner (1999) argues SBIR funding plays a certification role by conveying information about a startup's quality to VCs. Howell (2017), on the other hand, finds initial Phase I SBIR funding enables startups to prove the viability of their project to VCs. In contrast, the Phase II grants, which constitute 80% of the total SBIR funding, do not have an impact. The inefficiency of Phase II SBIR grants highlights that not all public funding is equal, and the focus and design of the funding matter. For example, Akcigit, Hanley, and Serrano-Velarde (2020) propose that the government's funding targeted at basic research is welfare-improving, whereas subsidizing applied research, which the private sector could otherwise finance, is less effective. This insight informs our distinction between Lerner (1999) and Howell (2017), who study direct R&D subsidies to businesses, while our work focuses on public funding targeted at basic science. Such funding creates a public good that has yet to spill over into the commercialization and entrepreneurial processes. These externalities are crucial as Myers and Lanahan (2022) document that publicly funded R&D generates significant spillovers, even in distant technological areas.

Babina et al. (2023) is another related study. They find that private financing *substitutes* for public funding and the rate of academic entrepreneurship drops when federal funding for academic research is cut.[23] Our results, however, suggest public funding can spur private investments and high-tech entrepreneurship, indicating a *complementary* effect. This could be due to the different settings of these two studies. We examine a large, long-standing positive shock aimed at resolving a major scientific bottleneck, whereas they focus on smaller-scale temporary negative shocks. Additionally, their focus is on the impact of public funding on the transition of academics into entrepreneurship, while our investigation centers on the response of VCs and the broader market.

2. Institutional Settings: BRAIN Initiative

A year before President Obama's announcement on brain research, leading researchers in the field published an article in Neuron, the premier journal of neuroscience, proposing a global initiative to map the human brain (Alivisatos et al., 2012).[24] Up to that point, to understand neural activity, neuroscientists were using electrodes that sparsely sampled brain activity, typically capturing signals from one to a few neurons in a specific region. The article argues that understanding neural circuits, which can involve millions of neurons, requires observation at a multi-neuronal level, as single-neuron recordings are insufficient—akin to trying to understand an HDTV program by focusing on just one or a few pixels on the screen. The article suggests a large-scale effort to map neural circuits

[23] In supplementary tests, they examine the effect of temporary *positive* federal funding shocks on academic entrepreneurship but do not find significant results.

[24] An earlier draft of this paper had been circulated in 2012, acknowledging the initiative's roots in *Opportunities at the Interface of Neuroscience and Nanoscience*, a workshop organized in 2011 by the Allen, Gatsby and Kavli institutes. These institutions are major philanthropic foundations funding cutting-edge basic science research. The initiative's emergence from such institutions highlights the role of other non-profit institutions in promoting basic science.

could lead to a major scientific breakthroughs:

> *"Emergent-level problems are not unique to neuroscience. Breakthroughs in understanding complex systems in other fields have come from shifting the focus to the emergent level. Examples include statistical mechanics, nonequilibrium thermodynamics, and many-body and quantum physics. Emergent-level analysis has led to rich branches of science describing novel states of matter involving correlated particles, such as magnetism, superconductivity, superfluidity, quantum Hall effects, and macroscopic quantum coherence. In biological sciences, the sequencing of genomes and the ability to simultaneously measure genome-wide expression patterns have enabled emergent models of gene regulation, developmental control, and disease states with enhanced predictive accuracy. We believe similar emergent-level richness is in store for circuit neuroscience. An emergent level of analysis appears to us crucial for understanding brain circuits. Likewise, the pathophysiology of mental illnesses like schizophrenia and autism, which have been resistant to traditional, single-cell level analyses, could potentially be transformed by their consideration as emergent-level pathologies."* (p.973)

These ideas were formally consolidated into an action-based proposal, published in Science[25] by the same team, which laid the groundwork for the BRAIN Initiative, unveiled in April 2013 by President Obama. Interestingly, five months later, the European Union launched a brain research development program known as the Human Brain Project (HBP). Despite their similar focus, the two projects exhibit distinct characteristics. Theil (2015) and Modic and Feldman (2017) provide a detailed comparison of their backgrounds and differences. The overarching goal of the BI is to map the human brain, while HBP's goal was far more ambitious to simulate the human brain, which many found unrealistic. BI was rooted in the interactions and consensus of a wider neuroscience community, while HBP was an initiative led by a few neuroscientists. This highlights the importance of consensus decision-making in setting the mission for such programs. Additionally, the process leading to the BRAIN Initiative's designation as a *Grand Challenge* in the US was more transparent than its European counterpart. Consequently, the BRAIN Initiative quickly gained popularity within the US neuroscience research community, while the HBP faced considerable controversy in the EU. In 2014, 750 European researchers signed an open letter to the European Commission criticizing the HBP's overly narrow focus and threatening to boycott the project (Guardian, 2014). Although the HBP continued until 2023, it appears to have had minimal impact on the European neuroscience community (Atlantic, 2019), whereas the BI, which is set to end in 2026, has already been applauded by the neuroscience community (Nature, 2021).

[25] Alivisatos et al. (2013)

Initially, the funding level for the BI was announced at $4.5 billion over a period of 12 years (NIH, 2014b). Based on agency budget reports, grant data, and BI fact sheets, we estimate that the US government has invested over $5 billion in basic neuroscience research between 2014 and 2022. While multiple government agencies, including NSF, DARPA, IARPA, FDA and Department of Energy were involved in the initiative, not all of them were active funders.[26] Details on annual funding levels by the agency are provided in Appendix A. NIH is the leading and central agency with 62% of the total funding with a working group that actively coordinates and evaluates the program.

Although the BI represents approximately 10% of the NIH's overall neuroscience expenditure, its significance extends beyond its relative size. Referred to as the "*moonshot between our ears,*" the BI focuses on the critical and underexplored area of mapping brain activity (Mott, Gordon, and Koroshetz, 2018). In Section 3.4, we compare NIH-funded publications in neuroscience outside the BI to BI-funded publications and find that BI-funded publications have higher impact. As one example, BI's Cell Census Network identifies the diverse cell types in human, monkey, and mouse brains. An editorial in Nature (2021) highlights this project as a significant advance in understanding structure-function relationships in the mammalian brain, poised to drive innovation in future neuroscience studies across various domains. Another distinction of BI from previous grants is the wide range of science it funds, encompassing fields from neurobiology to statistics, physics, chemistry, mathematics, engineering, and computer and information sciences. These distinct features set the program apart from previous neuroscience grants.

Beyond its direct scientific contributions, the BI has spurred the development of critical research infrastructure and resources. The foundational proposal published in Science acknowledges that achieving the goal of mapping the brain *"...require developing methods for storing, managing, and sharing large-scale imaging and physiology data, as well as developing methods for analyzing data and modeling underlying neuronal circuits, leading to emergent principles of brain function. It will be carried out by providing access to all investigators, including cellular, systems, and computational neuroscientists, to the methods and data needed for developing, testing, and verifying theories of how the brain operates."* In line with this direction, BI has contributed the development of new tools for capturing brain activity data and platforms for openly disseminating this data. For instance, Google Research has collaborated closely with BI scientists to develop computational tools for managing one of the BI datasets, sized at 25K terabytes (Januszewski, 2023). Also, BI's open-source data-sharing policy mandates awardees to disseminate their data on designated BI data archives, promoting

[26] For example FDA supports the initiative by enhancing the transparency and predictability of the regulatory landscape for neurological devices and assisting developers and innovators of medical.

knowledge spillover (NIH, 2019) within the neuroscience community and outside.

3. Sample and Data

Our dataset encompasses VC investments, VC-backed startups, their patent portfolios and employees, research grants from NIH and NSF, publications generated by these grants, and co-authors of these publications. We begin with the universe of VC deals in PitchBook and identify startups backed by VC (Section 3.1). We collect information on the patent portfolios and employees of these startups from PatentsView (Section 3.2) and the LinkedIn dataset (Section 3.5), respectively. We also incorporate research grant data from NIH and NSF (Section 3.4). Moreover, we identify *Neuro startups* by examining the patent portfolios of startups (Section 3.3).

3.1. VC-backed startups

Our study examines startups headquartered in the US from PitchBook. We include all companies with the first VC funding event from 2000 to 2019. The starting point is governed by PitchBook's reliable data. The ending point is chosen as the last year before the COVID-19 pandemic. Post-2019, the focus of public and private funding shifted towards funding COVID-19 treatment and vaccine R&D; this could potentially confound our analysis. We follow the VC exits on these investments until 2022. To be considered, a financing round must (1) consist of new equity issuance, excluding rounds focused solely on debt or secondary sales, and (2) be categorized as a "Venture Capital" round in the PitchBook dataset.[27] Our final dataset encompasses 50,601 distinct startups, with the founding years ranging from 1990 to 2019. VC-backed startups span 40 unique primary industry groups, with 65.02% of these startups concentrated in just five industry groups. The leading industry groups are Software, Commercial Services, Pharmaceuticals and Biotechnology, Healthcare Devices and Supplies, and Media, representing 37.22%, 10.35%, 7.65%, 5.74%, and 4.05% of the total number of VC-backed startups, respectively.

We are also interested in assessing whether the VC investment in the startup is successful. As with many VC studies, we cannot observe the exact amount returned to the VC to compare it to the amount invested. Nevertheless, we follow Ewens and Rhodes-Kropf (2015) and define a *Successful Exit* as one where the startup has either IPOed or been acquired with a reported exit value greater than two times capital invested and zero for smaller. Ewens, Nanda, and Stanton (2023) identify a startup as a failure when it has not raised capital three years after its financing round. Our *Successful Exit* dummy also

[27]For example, we exclude rounds primarily financed by angels, incubators, crowdfunding investors, corporate investors, and grants.

takes the value of zero for these startups. For this group, we follow Ewens and Sosyura (2023) and use the beta distribution to assign a failure/exit date between 2 and 5 years after the last financing event.

The dataset contains 94,565 unique financing deals with non-missing values in round sizes. Table 1 provides summary statistics of the variables in our analysis. The first financing round has an average round size of $4.57m at a pre-money valuation of $12.78m. Unsurprisingly, when considering all financing rounds, the average round size goes up to $9.93m, alongside a pre-money valuation of $80.51m, indicating that subsequent VC rounds generally have larger round sizes and higher pre-money valuations than the first round. The distribution of these variables is highly right-skewed. The number of VCs per deal averages 1.77 in the first round, rising to 2.17 in later rounds.

3.2. *Innovation*

We construct the startups' patent portfolios by connecting them to the PatentsView and augment them with the patent dataset from Ewens and Marx (2023). PatentsView provides extensive information on US patents granted between 1976 and 2023, including patent number, application and grant year, citations, Cooperative Patent Classification (CPC), assignees, and inventors for each patent.[28] To link PatentsView with startups, we employ a two-stage process. The initial phase involves matching the legal names of startups with the assignee names listed on patents, given that legal names represent the formal identification of startups and patent assignees denote the owners. We utilize the name-matching algorithm described in Tumarkin (2020) to pinpoint the closest matches between startups' legal and assignee names. Recognizing the potential for closely similar names among different startups, the subsequent step involves comparing the location of the patent assignee with the startup headquarters. A patent is considered associated with a startup when there is a match in both name and location, ensuring an accurate linkage between patents and the corresponding startups. To further refine our dataset, we combine our startup's patent dataset with a comprehensive patent dataset from Ewens and Marx (2023), which details the founding years for 85% of US-based assignees in PatentsView and links them to PitchBook startups. Our final sample of patenting startups includes 9,790 startups with an average of 12.91 patents per company.

Furthermore, our study utilizes the Artificial Intelligence Patent Dataset (AIPD) constructed by Giczy et al. (2022), identifying patents that have utilized AI in their innovation process. AIPD uses machine learning to analyze all US patents from 1976 to 2020 and pre-

[28]Our study specifically focuses on utility patents as per the March 2023 version of the PatentsView dataset.

grant publications (PGPubs) up to 2020. A unique advantage of AIPD is that it assesses the AI components in patents not just through abstracts and citations but also by considering the patent claims. The patent claim is important to consider as claims define the legal scope of the invention (Giczy et al., 2022).

3.3. *Neuro Startups*

There is no specific industry classification in PitchBook that allows us identify startups in the neuro space.[29] For this purpose, we primarily rely on startup patents. Startups usually have a narrow technological focus and one product. Therefore, it is fair to assume that a startup with a neuro patent is in this space. We define a startup as a *Neuro startup* when it has at least one patent in a neuro-related technology group. Neuro-related technology groups are those where the title of the CPC technology group[30] contains one of our *Neuro keywords*: {*neuro, nerve, brain, optogenetic, Parkinson, Alzheimer, and dementia*}. We obtain these keywords through the following procedure. PitchBook offers a keyword column for every startup. We compile all the keywords of a startup as long as one of them contains *neuro* or *brain*. This results in a vector of 500 keywords .[31] Next, we feed these keywords into ChatGPT and ask it to sort them based on neuroscience relevance. We subsequently manually check these and filter out those that introduce noise.[32] In total, we find 220 neuro-related CPC technology groups. These help us classify 1841 startup patents in neuro space, which relate to 755 startups that we call *Neuro Startups* and form our treated group. Of these startups, 88% are in the healthcare sector and 8% in the IT sector. Our sample features well-known *Neuro startups* like Neuralink, Lumos Labs, and Neurotrack Technologies, which have gained significant media attention.

To exclude large companies with patents in many areas, we do not count companies that obtained their first *Neuro* patent after VC exit. Our results are robust to a more rigorous definition of *Neuro startups* that captures patent timing. Under this definition, a *Neuro startup* must file for a patent in a five-year window after the first VC round. The limitation of this method is that we might lose startups whose R&D have longer timelines or those that choose to reveal their IP through patents later in their life cycle.

As an alternative classification of *Neuro startups*, we also consider relying directly on

[29] Due to the rise of neuro space, later versions of PitchBook, which we do not have access to, have added *neurotechnology* as an emerging space.

[30] One advantage of using CPC instead of directly analyzing the patent's text is that CPC standardizes the text and therefore we can identify the neuro space in a consistent way across all patents.

[31] These are not just one word and could be ngrams. For example: *Alzheimer testing, brainwave technology, neuromuscular disorder, vascularized tissue perfusion, or insurance automation*

[32] For example, the word *neural* could also pick up the AI related term *neural networks*. Therefore, we exclude the term neural.

PitchBook's business descriptions or keywords provided by PitchBook. While the findings using the classification are consistent with the patent-based definition, we prefer the patent portfolio approach because the business description keywords are subject to PitchBook's information, the source of which is unknown to us. Our comparison of different versions of PitchBook reveals that a startup's description slightly varies over time. This could be problematic if startups self-select to describe themselves with fashionable words. We do not face this problem with patents, as the underlying claims have been professionally examined and are legally binding and time-invariant.

3.4. Research grants

We gather detailed information on NIH and NSF BI grants, as well as non-BI neuroscience grants from NIH. This process is detailed in Appendix A.1 and A.2. Other agencies that support the program do not provide grant-level information. These two agencies have provided the lion's share of funding, with NIH providing significantly more. Collectively, NIH and NSF allocated $4.3 billion and an average of $1.1 million per project from 2014 to 2022. For publications resulting from these grants, 82% of projects funded by NIH have produced publications totaling 7,448 unique publications. Meanwhile, NSF's 694 BI grants have resulted in 6,138 publications. Besides, We collect additional details such as titles, citation counts, publication years, authors' names, and affiliations from Scopus (Rose and Kitchin, 2019), enhancing our dataset with this comprehensive information.

Besides directly funding impactful research, BI has also facilitated the interaction of data science and neuroscience, as references in Section 2 suggest. We also find evidence for this by comparing the focus of grants under NIH non-BI neuroscience research with that of the BI. We define grants with a data focus as grants that contain the following keywords: {*data science, machine learning, artificial intelligence, data set, data sharing, large datasets, large scale data, deep learning, software, algorithm, open source, and Python*} in project terms. We find that BI-funded grants are three times more likely to address data challenges in neuroscience compared to non-BI: 46.19% of grants in BI compared to 15.01% in non-BI. This significant discrepancy highlights BI's role in boosting neuroscience's practical application.

3.5. Employee of startups

Our primary source of data for startup employees is Revelio Labs, which has collected and augmented LinkedIn data. We can link 80% of all startups and 86.48% of all *Neuro* startups in our sample to Revelio Labs data. This enables us to learn about the startup's employees and their CVs.

We aim to identify the employment history of startup's inventors, founders, and authors under publications of BI grants. Thus, we integrate PatentsView and Scopus data on an individual level with Revelio Labs. Specifically, we aim to accurately pair individuals from two distinct groups: one comprising all startup employees listed in the LinkedIn dataset and the other encompassing all inventors of startup patents from PatentsView, alongside authors of BI-funded publications recorded in Scopus. To ensure precise matches between these groups, we begin the process by comparing their names and employment histories. A match is confirmed when two individuals share similar names and their employment histories overlap. For example, suppose inventor A shares a similar name with employee A, and inventor A has a patent with company ABC, while employee A works for company ABC. In that case, we establish a match between inventor A and employee A due to their similar names and shared employment history.

We first pair individuals by assessing the similarity of their names through fuzzy matching, with the methodology detailed in Appendix 6. Subsequently, we compare the employment histories of startup employees, inventors of startups, and authors of BI-funded publications. For inventors, we consider the names of patent assignees as their employment, as a patent assignee is typically the patent owner and the inventor's employer. Similarly, we use the listed affiliations of BI publication authors to represent their employment history. We identify 60,371 startup employees as inventors and 2,983 employees as co-authors of BI grant-derived publications.

3.5.1. Academic Startups and Inventors

We identify a startup as an *Academic Startup* if it has an academic employee in the first three years after being founded in a senior position. We define a senior position based on Revelio's seniority level, categorizing positions with a seniority level above 5, where maximum is 7, as senior roles. An academic employee is one who 1) holds a PhD in STEM degree and 2) has worked at a university under job titles such as {*professor, graduate, lecturer, academic, researcher, faculty, dean, instructor, scholar, scientist, postdoc, PhD, doctor, researcher, fellow, educator*}. Additionally, we identify employment at universities and research institutes by evaluating whether employer names include keywords like "university", "institute of technology," and "college," as well as specific abbreviations and names such as "UCLA," "MIT," and "Caltech," and terms such as "Lab," "Research," and "Mayo Clinic." Besides, We also identify the inventors of every startup's patents from USPTO. After linking these inventors to Revelio Labs, based on the same filters as above, we identify academic inventors.

4. Commercial Potential of BI Through Machine Learning

We start our analysis by understanding the commercial impact of BI-funded research. The first measure we use counts the number of patents citing an academic article. This data is provided by Marx and Fuegi (2020, 2022). The second measure is developed by Masclans et al. (2024) which predicts the ex ante commercial potential of an academic paper. We then compare these impact measures with that of other publications in neuroscience that are funded by NIH but are not part of the BI.[33] We refer to the latter group as non-BI neuroscience. This data serves as a reference point and helps us control for unique features of the field. For example, medical research publications generally receive more citations than those in other disciplines. Or, the availability of funding across different fields can affect their commercialization. By focusing on NIH grants in the neuroscience field, we can compare the outcomes of publications by the main agency behind the BI within the same research domain more accurately. In Appendix C, we validate BI's commercial and scientific relevance, using the above two measures. We find that BI-funded publications on average receive four times more citations compared to non-BI neuroscience and have higher commercial potential as predicted by the Masclans et al. (2024) measure.

We next examine whether startups effectively utilize the knowledge from BI publications. Given the fundamental nature of BI research, using the patent citation of BI research could be overly conservative and underestimate the broader impact of BI research. Lerner and Seru (2021) show that patents typically cite prior art directly related to the invention. This implies that the broader scientific foundation underlying the invention is less often cited. To overcome the limitation of patent citations, USPTO's chief economist argue that machine learning is a superior method for identifying patents in specific areas (Toole et al., 2020). Therefore, we develop a large language model (LLM), with the aim of identifying *Neuro patents* that are influenced by the BI publications. The LLM we use is SciBERT, a BERT model trained on 1.14M scientific articles (Devlin et al., 2018). Given its capacity to understand technology-related text, the SciBERT model is superior to the original BERT model. We further fine-tune the SciBERT model to calculate a score between 0 and 1 for the influences of BI on a patent. To avoid this look-ahead bias, we develop a separate model for every year from 2015 to 2020, such that the patents are only influenced by the knowledge generated up to that point. For example, a patent in 2017 cannot be influenced by the knowledge generated in 2018.

Supervised machine learning models typically require a balanced labeled dataset for

[33] See Section 3.4 and Appendix A for more detail

effective training (Lemaitre, Nogueira, and Aridas, 2017; He and Garcia, 2009). In our study, the positive cases are BI-funded papers, constituting a relatively small fraction of the overall publication pool. We randomly select papers from non-BI neuroscience grants to address the potential sample imbalance that would arise from including all other publications as negative cases. Publications from non-BI neuroscience grants are a strong baseline for distinguishing between the influence of BI and other grant-funded research (Masclans et al., 2024; Giczy et al., 2022). All the negative cases are papers published between 2009 and 2013, which proxy for the pre-existing neuroscience. Our results are robust when using alternative randomly selected negative cases.

We further divide our labeled sample into three sets: 80% for training, 10% for testing, and 10% for validation. We report the model performance in Table A4. All other models achieve a weighted average F1-Score above 0.9, which shows high accuracy for the model's predictions. In addition to conventional machine learning performance metrics, we also validate the performance of our model using patent citations. Patents that directly cite BI publications are highly likely to be influenced by BI research. Consequently, we tested whether our model could accurately predict patents that directly cite BI publications as patents influenced by BI research. Our model correctly predicts that 87.54% of these patents are influenced by BI research. Using our trained model, we find that 66% of neuroscience-related patents of startups are influenced by BI research.

5. Empirical Analysis and Results

In a difference-in-differences (DiD) setting, our empirical analysis compares the treatment effects of an exogenous increase in public funding of the treated with control groups. The exogenous shock we study is the BRAIN Initiative, a mission-oriented government program that aims to map the human brain. The outcome variables we study relate to private financing, labor, and innovation outcomes of the *Neuro startups* with control groups. The selection of control group in a DiD study is crucial to isolating the treatment effect from other confounding influences. In our study, the baseline control group comprises all non-Neuro VC-backed startups. VC backing is a proxy for the startup's growth potential as a small fraction of young companies manage to receive venture capital. This group also provides a broad comparison across diverse sectors to distinguish the overarching patterns that differentiate *Neuro startups*. To further enhance the comparability, we refine this control group in three ways. First, we only include startups within the Healthcare sector. This sector, primarily composed of life science companies, is inherently research-intensive and, like the neuro segment, relies heavily on scientific breakthroughs and developments. Hence, startups in this sector can serve as a more relevant benchmark when assessing the unique impact of public funding on *Neuro startups*.

Second, the time frame surrounding the BI provides a proximate economic context and, therefore, must be carefully selected. By choosing a window of five years before and after the policy implementation, we capture a temporal environment closely aligned with the period of interest. Third, given that our definition of a *Neuro startup* depends on the presence of patents with *Neuro keywords*, and considering that only about 15% of startups hold patents while receiving VC investment, we refine our baseline control group for a more precise comparison. Startups that possess at least one patent during the VC investment period represent a more similar cohort to *Neuro startups* because patenting indicates engaging in certain type of innovation, where the IP protection is central to the value proposition of startups in the eyes of investors.

5.1. *VC Investments: Financing and Valuation*

We start with the VC financing outcomes of *Neuro startups* as the first-order effect we are examining. We test the hypothesis that the public funding that BI provides increases the investability of *Neuro startups* for the VCs compared to the control group. The measures of investability, we study are the amount that VCs invest in the startup and the valuation of the startup at the financing. For this test, we estimate the following equation at the financing round level:

$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t + \beta_2 X_{it} + \gamma_t + \rho_j + v_{ijt}, \tag{1}$$

where X_{it} are entrepreneurial firm characteristics at the time of the investment, including industry code fixed effects, geographic fixed effects, and an indicator for whether the firm was a *Neuro* startup (i.e., treated), γ_t are year fixed effects corresponding to the year of the investment. The main coefficient of interest (β_1) is the interaction between *Neuro* and *Post*. It is worth noting that Pitchbook offers three levels of industry classification, with the broadest being the industry sector (akin to SIC2), followed by an industry group (akin to SIC3) and an industry code (akin to SIC4). Healthcare is one of seven industry sectors and is the second largest in terms of number of VC-backed companies after IT.[34] Our industry fixed effects are at the more granular level of industry groups.[35]

[34]Other sectors include Information Technology, Healthcare, B2B, B2C, Energy, Financial Services, Materials, and Resources.

[35]While our results are robust to the choice of industry level, this level balances the need for specificity without excessively absorbing the variation we aim to capture, which might occur with the most granular Industry Code classification. Employing Industry Group fixed effects, which consist of 40 different categories, allows us to control for industry-specific trends and characteristics without overshadowing the treatment effect of interest.

The first Y_{it} we study is the amount the VC invests at a financing round, i.e., round size. We focus on the first financing round for several reasons. First, the investor uncertainty is highest prior to the first investment. Given the active involvement of VCs in their investments, after the first investment, the VC acquires information about the startup's quality. Also, the first investment is more likely to be based on the promise of the startup's technology and less on market validation. Initially, the uncertainty is highly skewed towards scientific and technological feasibility, which is where BI is most relevant. If BI has reduced the technical uncertainty of startups in the funded area, we would expect this to lead to larger investment amounts in the first round.

In Panel A of Table 2, we report the results of the OLS regression of Equation 1. The outcome variable, first round size, is log transformed to account for its skewness. We include year, state, and industry group fixed effects. In our specifications, we also control for the number of VCs that are active in the funding to control for the fact that a larger syndicate can provide larger funding amounts. In Column (1), we include all VC-backed startups in the sample. In Column (2), we limit the sample to startups in the healthcare sector, which offers a closer control group. In Column (3), we only include five years before and after the shock in the healthcare sector for a balanced sample. VC-backed startups are predominantly in the IT sector, where patenting is rare. Therefore, in Column (4), we require the control group to have at least one patent. These *Patenting* startups are also a reasonable control group that is more likely to rely on basic science.

The *Neuro* $\times$ *Post* interaction term, which captures the incremental effect on *Neuro startups* post-BI, is significantly positive across all specifications. Specifically, the coefficient ranges from 0.495 in the overall sample to 0.392 in the healthcare sector. These coefficients suggest that ceteris paribus, *Neuro startups* have seen an increase in the amount of first-round financing by approximately 39.2% compared to other patenting startups in the healthcare—which offer the closest control group to *Neuro startups*— to 49.5% compared to all other startups, post-BI. This result is statistically significant at the 1% to 5% levels.

While these results show that VCs make larger investments in *Neuro startups*, it does not necessarily mean the underlying science is of more value in the eye of the markets. It could be that due to changes in R&D costs, *Neuro startups* have larger capital requirements to finance their operations. As such, we next turn to valuations, which also reflect the uncertainty associated with neurotechnologies. In Panel B of Table 2, we report the results from OLS regressions, paralleling the structure used for analyzing financing size, but this time focusing on the pre-money valuations; i.e., valuation at the financing event net of the VC's investment amount. Again, we employ log transformation to mitigate the impact of skewness. The *Neuro* $\times$ *Post* interaction term is significantly positive, indicating a robust post-BI increase in the valuations of *Neuro startups* across the first financing rounds. Specifically, Panel A shows that first-round financing post-BI sees valuation increases between 41% in the healthcare sector and 35.8% across the overall sample. This significant uplift, noted at the 1% to 5% levels, highlights the BI's strong influence on enhancing the perceived value of *Neuro startups*. These valuation increases post-BI for *Neuro startups* are pivotal as they not only indicate an augmented investment scale but also reflect market sentiment regarding the potential and reduced technology uncertainty associated with these startups. A higher valuation typically denotes greater market confidence, likely stemming from advancements in basic science funded by initiatives like the BI. This enhanced confidence could be due to the BI's role in reducing the R&D uncertainty, offering more robust scientific foundations for *Neuro startups*, and increasing the attractiveness of these ventures to VCs.

Nonetheless, subsequent rounds are also important to see if this initial boost translates into an ability to attract further capital over time. This can signal sustained investor confidence and the potential for scale. Appendix Table A6 presents a robustness check by extending the analysis to all financing rounds. To control for the startup's life cycle and the increase in round size with the startup's progression, we control for the round number (i.e., 1st round, 2nd round...) through fixed effects. Panel A of Appendix Table A6 shows similar results to the first round; the $Neuro \times Post$ coefficient remains positive and significant. Also, Panel B extends the valuation analysis to all rounds and finds valuation increases range from 10.6% to 24.1%.

5.1.1. Parallel trend Assumption of BI

As with any DiD estimation strategy, our key identifying assumption is parallel trends, which is the "untreated" industry-segments provide an appropriate counterfactual for what would have happened to the treated firms had they not benefited from the introduction of BI. While the parallel trends assumption, by definition, cannot be proven, we aim to validate it in several ways.

First, a condition for the validity of the parallel trend assumption is that without the treatment, the outcome of the treated and control units would have changed by the same amount if the outcome had not changed differently before the treatment between the treated and control units. Figure 2 shows the time series of VC financing for both Neuro and non-Neuro startups. For the assumption of parallel trends to hold, the paths of the Neuro and non-Neuro groups should not display systematic differences before the shock. In the graph, the two lines representing *Neuro* and *non-Neuro* startups appear to move similarly before the vertical line denoting the BI in 2013, suggesting that before the BI, the financing size and valuation were trending similarly for both groups. After the BI, however, there is a strong divergence, with Neuro startups receiving larger financing and at higher valuations than non-neuro startups. This divergence after the BI is consistent with the treatment effect we aim to measure.

We also estimate the dynamic version of Equation 1, replacing *Post* with year dummies. Figure 3 shows the coefficients where the control group is all other startups in the healthcare sector.[36] We keep a balanced sample seven years before and after the shock. The patterns in the figure show that there is no pre-trend and that the timing of the increase in financing amounts and valuation is consistent with the announcement of the BRAIN Initiative. There is indeed a significant spike in financing outcomes in 2013, while BI has not yet had any immediate scientific outputs. This surge can be explained by the elevated perceived upside potential of these firms. The BI likely acted as a strong signal of government commitment and potential future breakthroughs. VCs, who invest based on the future option value of their investments, could anticipate significant scientific advancements and commercial opportunities stemming from increased funding, regulatory support, and collaboration between academia, industry, and government.

An omitted variable that might drive both public and private investments could be market demand. Indeed, neural and brain-related conditions represent a substantial global health burden and economic cost. According to Collins, Patel, Joestl, et al. (2011), Schizophrenia, depression, epilepsy, dementia, alcohol dependence, and other mental, neurological, and substance-use disorders constitute 13% of the global burden of disease, surpassing both cardiovascular disease and cancer. Dementia alone cost the world up to $609 billion in 2009. Nonetheless, while this existing demand might incentivize investments in neuroscience, it is unlikely that such demand would have changed abruptly around the time of the BI's announcement to explain the initiative's timing and focus. In essence, while the market demand for neuroscience-based products was undoubtedly strong, the BI's designation as a *Grand Challenge* was a policy-driven priority shift, not a response to any sudden market demand change. Still, it could be argued that the market had anticipated such a policy due to the neuroscience community's activities, as detailed in Section 2. While the neuroscience community was actively developing the proposal that eventually became the BI, other scientific communities were engaged in similar endeavors. Such endeavors resulted in 12 distinct scientific projects, one of which was the BI. The top-down designation of BI, thus, presents an element of unpredictability and randomness, further supporting the shock's exogeneity.

[36] We repeat this excerise for all rounds and plot the estimates in Figure A.1.

5.1.2. *Alternative Classification of Neuro startups*

Relying solely on patents may cause us to overlook *Neuro startups* that never file for a patent. To address this issue, we use Pitchbook's descriptions to identify *Neuro startups* based on the same set of keywords. The classification process is detailed in Section 3.3. In the Appendix Table A8, we replicate the analysis from Table 2, and our results remain consistent. This approach also alleviates concerns about look-ahead bias.

This bias may arise because by using patent data for classification, we might label a startup as *Neuro startups* too early before it actually begins working on neuro-technology. In such cases, changes in VC financing might be unrelated to shocks in the neuroscience space. However, two assumptions underlying the look-ahead bias seem unlikely. First, unlike large firms, startups lack the resources to quickly switch between technological areas; they typically focus on innovating within a narrow technology and a few products. Second, patents are the outcomes of R&D processes that take a long time. VC are usually well-informed about a firm's focus and are aware of its pipeline before investing. Therefore, our baseline approach of classifying startups with a neuro patent before the VC's exit seems reasonable.

Nevertheless, in Appendix Table A7, we revisit the results from Table 2 by defining a *Neuro startups* as a firm that files for a neuro patent within the first five years after its founding. Our results still hold for this sample. The advantage of our baseline classification is that, by not narrowing the classification timeline, we avoid excluding startups whose R&D takes longer to reach the patenting stage. Moreover, using patents over Pitchbook's descriptions has the benefit of relying on legal documents that have been verified by examiners. While Pitchbook descriptions are generally informative, we believe patents are superior in our context.

5.1.3. *Robustness Tests*

An alternative story for the more favorable VC financing could be because *Neuro startups* are operationally more established at the time VCs finance them. Under this scenario, the lower operational risk, a signal for quality, is the reason for larger round sizes, rather than R&D risk. We examine this possibility by checking the business status of the startup at the time of financing. We construct a dummy called *Generating Revenue*, which is equal to one if the startup has revenue at the round. PitchBook designates the startup's business status as either "Generating Revenue" or "Profitable" at a given round. The other categories mostly include cases where a startup's business status is designated as

"Startup", "Product Development", "Product in Beta Test" or "Clinical Trial".[37] We examine whether the startup is generating revenue at the round. The results are reported in the Appendix Table A9. Contrary to the story above, we find that *Neuro startups* are less likely to be generating revenue at the time of financing. This suggests that after the BI, VCs are more comfortable with funding *Neuro startups*, which are operationally less developed but perhaps have a lower R&D risk.

5.1.4. Startups with BI scientists

Thus far, our results show that post-BI *Neuro startups* became more attractive for VC investments. Here, we provide a more direct link between the BI as a boost to the startup's human capital and VC financing. We exploit the heterogeneity of *Neuro startups* in their exposure to BI, by identifying those that employ BI scientists. We call this group *BI Employer* and hypothesize that *BI Employer* benefitted directly from the BI by employing human capital that embodies the knowledge produced under the BI. Hence, we expect BI employers to be more attractive to VC than other similar *Neuro startups* without BI scientists. To test this hypothesis, we estimate the following equation for the financing round and pre-money valuation level:

$$Y_{it} = \beta_1 \text{BI Employer}_i \times \text{Post}_t + \beta_2 X \mathit{BI\ Employer} + \beta_3 X_{it} + \text{Fixed effects} + v_{ijt}, \qquad (2)$$

where *BI Employer* is defined as an indicator variable that equals one for *Neuro startups* employing BI scientists, and zero for those that do not. More specifically, the *BI Employer* can vary at the firm level as *BI˙Employer* becomes 1 from the year *Neuro startups* employ BI-funded research authors onwards. The key independent variable is the BI Employer $\times$ *Post*, which captures the incremental effect on *BI Employer* post-BI. X_{it} is the number of VCs in the round.

The results of this estimation are reported in Table 3. In Columns (1-3), we include industry, year, state, and round fixed effects, and we add firm fixed effects, in Columns (4-6). Panel A shows that *BI Employers* receive larger round sizes compared to other *Neuro startups* after BI. The coefficient of 0.538 in Column (1) suggests that *BI Employers* receive rounds that are 53.8% larger compared to similar deals in the same round, year, and industry by non-BI employers. Furthermore, We restrict our sample to all *Neuro startups* within the healthcare industry in column 2 and further restrict this to deals between 2008

[37] We verify that this categorization reflects a startup's degree of development by examining the mean revenue of startups in each category. The "Generating Revenue" and "Profitable" categories are indeed associated with an average revenue level that is several orders of magnitude larger than the other categories.

and 2017 and find similar results. In Columns 4 to 6, we introduce firm and year-fixed effects. The firm and year-fixed effects allow us to compare the change in deal size before and after employing BI scientists within the firm and mitigate the concerns that *BI Employer* has better quality than other *Neuro startups*. We obtain similar results under these specifications. These findings suggest that VCs provide more financing when the startup has acquired human capital that has presumably become more investable after the BI.

In Panel B, we repeat the same exercise for round valuation as the outcome variable. We observe a similar pattern here, too: VCs value *BI Employer* more than other similar *Neuro startups* without BI scientists after the BI. In Column (1), the coefficient of BI Employer $\times$ *Post* is 0.545 and statistically significant at 10%, suggesting that *BI Employer* has a larger pre-money valuation compared to other *Neuro startups* in the same industry and state. We compare *BI Employer* to *Neuro startups* in the healthcare industry in column 2 and find similar results in terms of economic magnitude. Specifically, *BI Employer* has a 55% larger valuation than other healthcare *Neuro startups* in the same industry. Column 3 reports the regression result estimated using samples from 2008 and 2017. The coefficient of column 3 is 1.072 and statistically significant at 1%. We include firm and year-fixed effects in Columns (4-6). While the coefficients are positive, they are not statistically significant.

5.2. VC Exits

While the results above indicate a surge in VC interest in *Neuro startups* post-BI, it is important to see if the broader market also recognizes this interest. VC funds typically exit their investment through an IPO, M&A, or write-off after a few years and return the proceeds to the fund investors. To the extent that BI makes neurotechnology more investable, this investability should also be reflected in the startup financial outcomes beyond venture capital. As such, we next study whether VCs exit their neuro investments more successfully after the BI.

Given that sell-outs are the primary type of exit in the last decade, we first examine whether BI affects the timing of sell-outs. Figure 5 illustrates the acquisition trends of *Neuro startups* in comparison to other healthcare startups over the sample period. Pre-BI, there were 32 acquisitions in the neuro space over a 13-year span, a figure that rose 5 times to 159 in the 7 years post-BI. In contrast, the broader healthcare sector experienced 840 acquisitions pre-BI and saw an increase to 990 post-BI. This trend indicates that the BI has likely heightened the appeal of neurotechnology to larger acquirers, who are now increasingly integrating these startups into their portfolios, suggesting a recognition of the commercial viability and promise of neurotechnology advancements. While acquisitions in other healthcare sectors also grow, the more pronounced and immediate increase in *Neuro startup* acquisitions post-BI underscores the initiative's impact in making neurotechnology a standout area for investment, demonstrating that both venture capitalists and larger market players acknowledge the potential fostered by the BI's focus on neuroscience.

Nevertheless, an acquisition does not necessarily indicate a successful exit for the VC as acquisitions with a low premium could disguise failure (Puri and Zarutskie, 2012). Thus, to measure success more carefully, we follow the definition of *Successful Exit* outlined in 3. Besides, the *time to exit* is an alternative measure of VC investment success, calculated as the log of the number of days between the first VC investment and the exit date. For every startup, we run OLS regression of these variables following Equation 1, where the year fixed effect reflects the first year the startup receives VC financing. We also add the year of exit to control for the endogenous timing of the exits. In our specifications, we also control the amount the startup has raised prior to exit. This control helps adjust for the size and scale of the startups at the time of exit, ensuring that the *Neuro* $\times$ *Post* coefficient does not merely reflect differences in fundraising.

Table 4 reports the results of this specification. The *Neuro* $\times$ *Post* interaction term is central to the analysis, as it measures the differential impact of the BI on the probability of a successful exit for *Neuro startups*. We progressively limit the control firms from Columns (1) to (4), the positive and significant coefficients across the board from 0.087 in the healthcare sector to 0.128 in the overall sample, indicating that post-BI *Neuro startups* have a significantly higher probability of achieving successful exits compared to pre-BI, reinforcing the hypothesis that BI has enhanced the investability of *Neuro startups*. The coefficients signify that the odds of a successful exit increase by 8.7% to 12.8% for *Neuro startups* post-BI, highlighting the positive impact of the BI on these firms' exit outcomes. These results support the findings of increased VC investments in *Neuro startups* post-BI and extend the narrative to the broader market's recognition of these startups' value, as evidenced by their exit outcomes. The significant *Neuro* $\times$ *Post* coefficients across various specifications suggest that the BI's influence goes beyond attracting initial VC interest, translating into tangible, successful financial outcomes for *Neuro startups*.

Columns (5) to (8) of Table 4 analyze the impact on *time to exit*. The coefficients of the *Neuro* $\times$ *Post* interaction term are negative and statistically significant, indicating a reduction in exit time ranging from 11.6% for patenting startups to 25.6% for the overall sample. These findings suggest that *Neuro startups* have a shorter time to exit after the BI. This shorter exit time aligns more closely with the finite investment horizons of VC, thereby enhancing the attractiveness of *Neuro startups* to VC investors.

5.3. *Mechanisms*

We have established that the BI enhances the attractiveness of *Neuro startups* for VC, evidenced by increased financing sizes, pre-money valuations, and success of the exits. To understand the mechanisms that elevate the investability of *Neuro startups*, we examine their characteristics, particularly characteristic that can be impacted by basic science breakthroughs. Our analysis centers on two key aspects reflective of the startup's underlying scientific foundation: (1) the human capital represented by academic scientists employed by the startup and (2) the innovation as shown by the startup's patent portfolio.

5.3.1. *Academic Startups*

The BRAIN Initiative primarily funds academic research. If BI has enhanced the commercializability of neuroscience, then academics – who are crucial for commercialization – are more likely to join startups. The presence of academics in startups not only brings specialized expertise but also serves as a strong signal of team quality to investors. This is important in light of the findings by Bernstein et al. (2017), who document that investors perceive a startup's human capital as a key early-stage indicator of quality. These arguments suggest that having academics as employees improves startups' attractiveness to VCs. Hence, we hypothesize that VC-backed *Neuro Startups* are more likely to have academics as employees especially in their early years. As outlined in Section 3.5.1, we define an *Academic Startups* as one with an academic in a senior position within three years of its founding. We broaden our focus beyond founders because senior academic researchers frequently join startups as advisors or occupy other senior roles.

In Table 5 we examine if post-BI *Neuro Startups* are more likely to be *Academic Startups*. Our focus here is capturing the engagement of academics with startups in the earliest stage of development, where uncertainty is high. Therefore, our *Post* variable is one if the founding year is 2013 or after, as opposed to the year of financing event. The results in Column (1) and (2) of Table 5 show that relative to all other VC-backed startups, post-BI *Neuro startups* are about 10% more likely to be an *Academic Startup*. However, despite the positive coefficient, in Columns (3) and (4), we do not find statistically significant results when we compare *Neuro Startups* to other healthcare or patenting startups. Figure 4, which plots the dynamic DiD estimates for the Column (3) specification, shows an upward trend in the likelihood of *Neuro Startups* becoming *Academic Startups* over time. A plausible explanation for the insignificant results driven by the earlier period could be that the effect of the BI for newly founded companies becomes more pronounced towards the end of the sample. This suggests that as BI produced more knowledge and advancements from this knowledge began to emerge, academics engaged more in *Neuro* *startups*.

5.3.2. *Innovation and Academic Inventors*

As another labor channel, we also examine the background of inventors, who work for *Neuro Startups*. We hypothesize that BI has increased the supply of skilled labor for *Neuro startups*. 10% of NIH's BI funds were explicitly allocated toward training skilled labor such as postdoctoral researchers. This number is likely an underestimate, as BI grants indirectly enabled principal investigators to hire PhD students. We proxy the supply of skilled labor using the number of newly hired academic inventors. To identify these inventors, we link USPTO's inventor data to Revelio Labs to track inventors with prior academic experience, as detailed in 3.5.

Beyond labor supply, we examine whether BI has directly enhanced the attractiveness of *Neuro startups* to the VCs by expanding their innovation portfolio. As we showed in Section 3.4, BI-funded research has successfully advanced the frontiers of neuroscience. To examine whether this scientific progress has translated into technological innovation, we study the patent outcomes of *Neuro startups*. The outcome variables we study include startups' number of patents and breakthrough patents. The breakthrough patents are those that receive more citations than the citations at the 90th percentile value within the same technology class and grant year. Furthermore, the BI's overarching goal – mapping the brain, a complex network – requires significant interaction between data science and neuroscience. We expect this interdisciplinary collaboration to have spillover effects such as the adoption of AI in the innovation processes of *Neuro Startups*. To proxy for the adoption, we rely on a measure developed by USPTO's economists: Giczy et al. (2022) have developed a machine learning method that determines whether the underlying technology in a patent has adopted artificial intelligence.

To test the hypotheses above we construct a panel of firm-year observations between the founding year of the startup to the year of VC exit, for all startups with at least one patent. We estimate:

$$Y_{it} = \beta_1 Neuro_i \times Post_t + \beta_2 X_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{3}$$

where for startup i in year t, Y_{it} includes the number of patents, breakthrough patents, and the number of academic inventors employed. Y_{it} following a Poisson distribution as a count variable with many zeros (Cohn, Liu, and Wardlaw, 2022). The main coefficient of interest (β_1) is the interaction between *Neuro* and *Post*. λ_i and θ_t are firm and year-fixed effects.

Table 6 reports the results of this estimation. Columns 1, 3, 5, and 7 restrict the panel to the window between the founding year and the year of the first VC investment. The goal is to understand the characteristics of startups before the VCs invest. This controls for the additional capital and resources that the company would have after receiving venture capital. In Columns 2, 4, 6 and 8, we keep all the years from the founding year to the year of VC exit.

We find that *Neuro startups* produce more patents, breakthrough patents, and AI patents and hire more academic inventors compared to other patenting startups after the BI. Columns 1 and 2 presents the Poisson regression of the number of patents on the interaction between *Neuro* and Post with startup and year fixed effect. The coefficient of the interaction in column 2 is 0.51 and statistically significant at 1%, suggesting that *Neuro startups* produce 1.67 ($e^{0.51}$) times more patents than other *non-Neuro startups* after the BI. Although *Neuro startups* produce a larger number of patents, this does not necessarily translate into higher quality patents. Therefore, we further evaluate the quality of patents by counting the number of breakthrough patents. These are the most influential patents for a given technology class and grant year. Columns 3 and 4 investigate the role of BI on the breakthrough patents of *Neuro startups*. The coefficient of column 4 is 0.661 and statistically significant at 1% level, suggesting that *Neuro startups* produce 1.94 ($e^{0.661}$) times more breakthrough patents after the BI.

Columns 5 and 6 report the results of regressing the number of academic inventors hired on the interaction of *Neuro* and Post. The coefficient in column 6 is 0.726, significant at the 1% level, indicating that post-BI, *Neuro startups* hire over two times more academic inventors than other startups. In Columns 7 and 8, we find *Neuro startups* produce more AI-driven patents than other comparable startups. More specifically, the coefficient in Column 8 is 0.824 and statistically significant at the 1% level, indicating that *Neuro startups* generate approximately 2.28 ($e^{0.824}$) times more AI patents as many AI patents as similar startups.

5.3.3. Adaptability of Neuroscience

As we outlined in Section 3.4, BI grants were more focused on data-intensive research. As such, we examine whether such emphasis is also reflected in the evolution of neurotechnology post-BI. We provide evidence that post-BI, neurotechnologies became more interdisciplinary and adaptable to other technologies, particularly AI and big data. Figure 6 illustrates the top 10 verticals in neurotechnology before and after the BI, highlighting a shift in the landscape of neurotech industries. Pre-BI, the neurotech field was concentrated mainly in traditional life sciences areas, with a modest representation in data-centric domains. However, post-BI, there is a discernible broadening of focus, with significant growth in AI and Machine Learning, Big Data, Wearables, and Quantified Self verticals. This expansion reflects the BI's influence in fostering a data-driven approach within neuroscience, aligning with its mission to advance our understanding of the brain through data-intensive research and interdisciplinary collaboration.

This shift is also mirrored in the acquisition patterns observed post-BI. Figure 5 shows the surge in the acquisition of *Neuro startups*. In Appendix Table A10, we examine the distribution of sectors to which these acquirers belong. We find a substantial increase in *Neuro startups* acquisitions—from 32 in the pre-BI period to 159 post-BI. While healthcare remains the dominant acquirer sector, there is a post-BI emergence of acquirers from diverse sectors such as IT, B2B, and B2C, reflecting an acknowledgment of the broader applications of neurotech innovations.

The enhanced focus on data-centric research and applications within the neurotech domain post-BI likely translates to startups with a higher potential for scalability. The expansion in the acquirer base reflects the expansion of neurotechnology beyond its healthcare origins. This broadened market appeal can enhance the perceived potential for returns on investment, thereby increasing the investability of *Neuro startups*.

However, the adaptability of neuroscience to AI and ML raises an omitted variable concern. While our sample period does not cover the post-ChatGPT AI boom, advances in AI and ML have attracted much attention from VCs in the last decade. As such, an alternative explanation for our results could be that VCs finance neuro startups more favorably not because of the BI but because neuroscience is a fertile ground for the application of AI. Under this scenario, our results should be driven by startups that apply AI and Big Data technology in neuroscience. To test this, we examine whether our results are robust to the exclusion of this startusp. In Appendix Tables A11 and A12, we repeat the exercise in Table 2, respectively. Our results are robust even if we exclude such startups.

We recognize that, historically, the knowledge spillover between AI and neuroscience has significantly contributed to the advancement of both fields (Hassabis, Kumaran, Summerfield, and Botvinick, 2017)[38] and ignoring the impact of AI on neurotechnology would oversimplify the dynamics at play. Nevertheless, the neuroscience community acknowledges the role of BI as a catalyst for the application of AI in neuroscience (Zador et al., 2023). AI and ML require large amounts of data for algorithm training. The substantial data generated under the BI and shared via the informatics infrastructure and requirements of BI has facilitated the application of AI and ML.

[38] The contribution is two-sided. The development of artificial neural networks (ANNs) has been substantially influenced by the structure and function of biological neural networks.

6. Conclusion

This study examines how strategic government investments can de-risk nascent technologies and stimulate private investment. In a difference-in-differences setting, we examine the Brain Research Through Advancing Innovative Neurotechnologies (BRAIN) Initiative, a government program with the goal of mapping the human brain. We find that VCs invest in neurotechnology startups with higher amounts and valuations post-BRAIN Initiative. VCs experience faster and more profitable exits from these investments, validating the promise of these investments beyond venture capital. The positive impact of government intervention explains these trends. Investors place a premium on the skilled labor unlocked via the program, particularly these academics transitioning into entrepreneurship. *Neuro startup* also produces more and better innovation outputs, which are more integrated with AI technologies.

These findings substantiate the importance of the government's role in providing basic science as a public good. Specifically, our causal evidence highlights mission-oriented programs as an effective mechanism for delivering public funds. Public funding for neuroscience research was available even before the BRAIN Initiative. In fact, the initiative itself comprises only about ten percent of the total neuroscience public funding. Nonetheless, the efficacy of BI suggests that coordinated, targeted programs – where a consensus in the scientific community sets the target – can resolve coordination failure that precludes private investments. Furthermore, BI generates technological spillovers beyond the specific goal of the program, highlighting the social benefits from the serendipitous nature of basic science research.

Our focus on the BRAIN Initiative leaves open the question of how similar initiatives perform in other emerging technological fields, especially those with greater demand uncertainty. Future research could compare the optimal design of such interventions across domains that vary in demand uncertainty (e.g.,quantum computing or synthetic biology). Such studies could inform policies aimed at bridging the gap between basic science and commercialization, ultimately maximizing the economic and societal impact of public investment in innovation.

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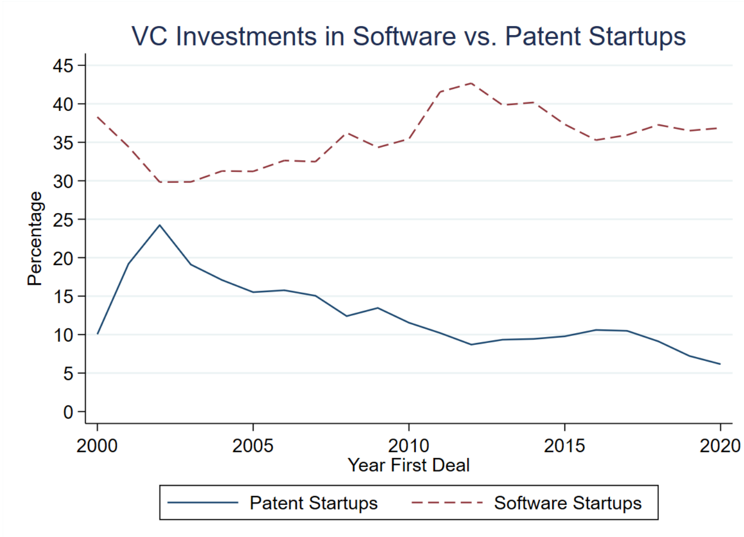

Figure 1. **VC Investments in Software vs. Patent-holding Startups**

This figure plots the percentage of US startups holding patents against those identified within the software industry sector over time, based on the year they received their initial venture capital funding. The solid line represents startups with patents, while the dashed line indicates software-focused startups, as classified by PitchBook industry groups.

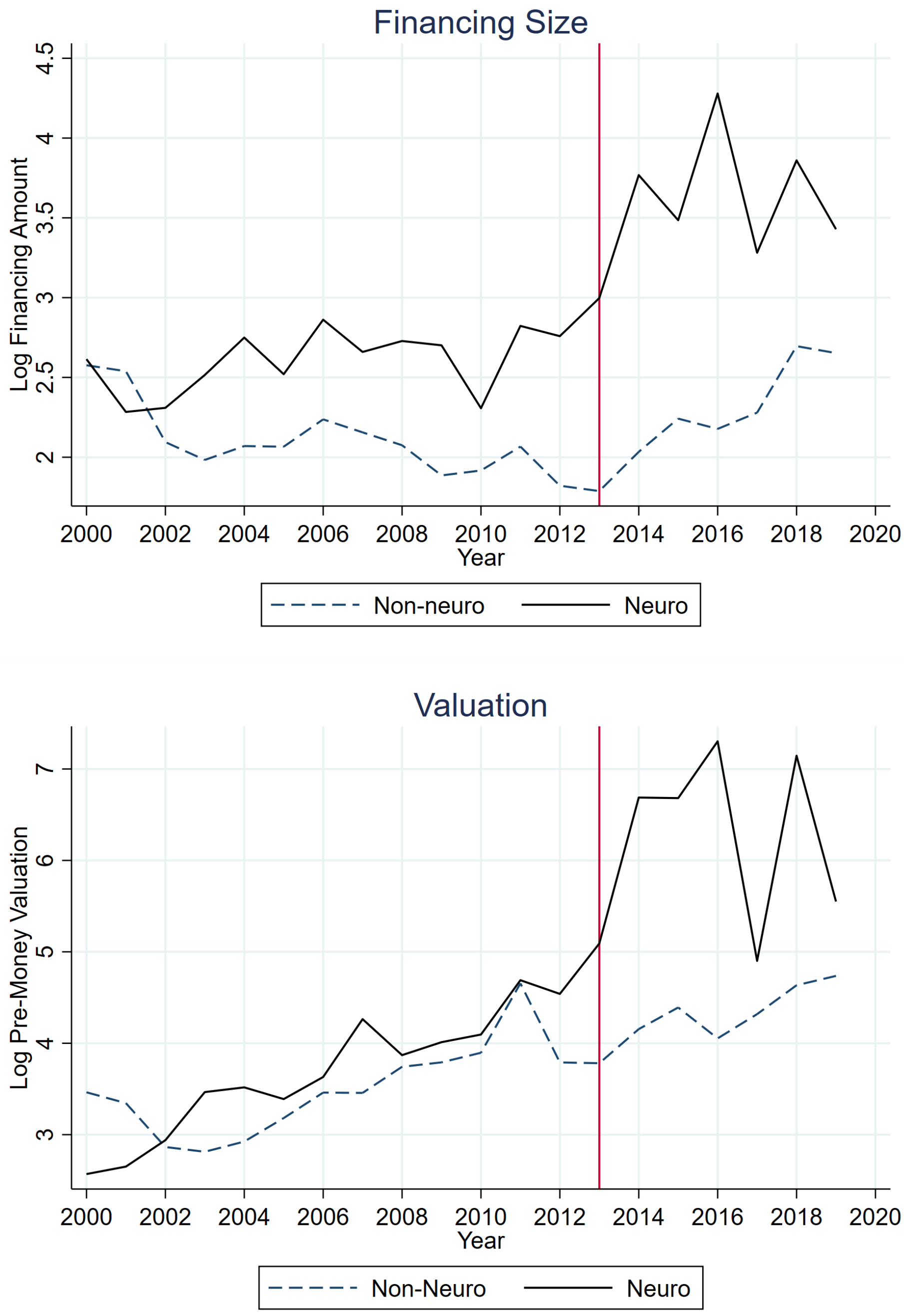

Figure 2. **Financing and Valuation of Neuro-Startups**

The figure above shows the log of the average amount of VC financing rounds for neuro startups (solid line) and all other startups (dashed line). The figure below shows these values for the average amount of Pre-Money valuation. The red line is on 2013, the announcement year of the BRAIN Initiative.

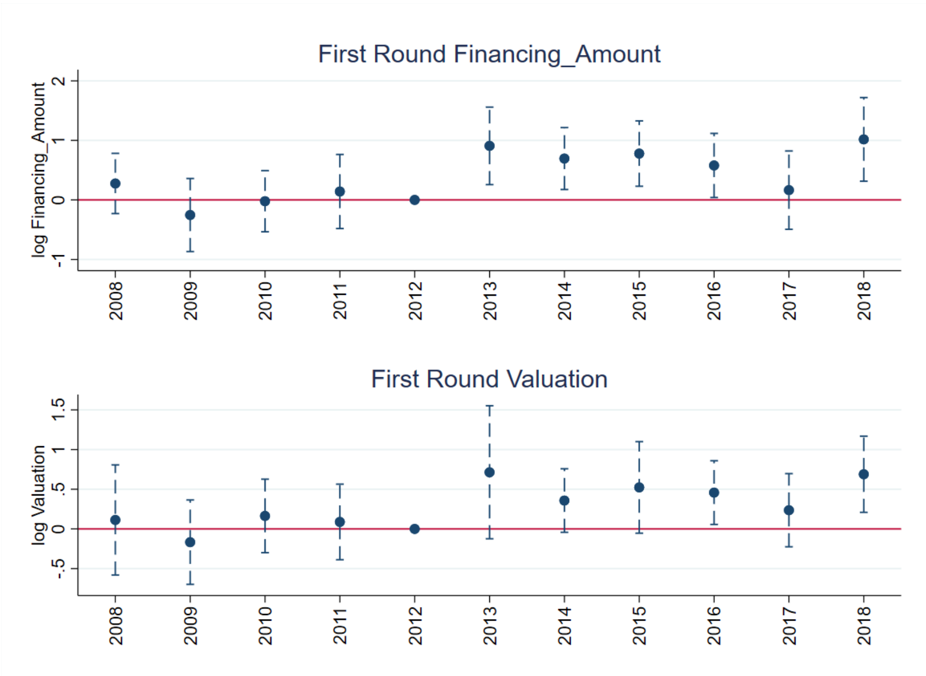

Figure 3. **Difference-in-difference estimates for financing and valuation: Neuro vs Other Healthcare**

The figure plots the coefficients for the estimation of dynamic version of Equation 1, with interaction terms of each financing year and the *Neuro* dummy where the dependent variables are the log of the financing amount and the log of the pre-money valuation. The figures only include the first rounds. The unit of observation is an entrepreneurial firm's first financing event. The 2012, i.e. t=(-1), interaction term is the excluded category, reported as zero in the figure. The vertical lines represent the 95% confidence interval for the coefficient estimates with robust standard errors.

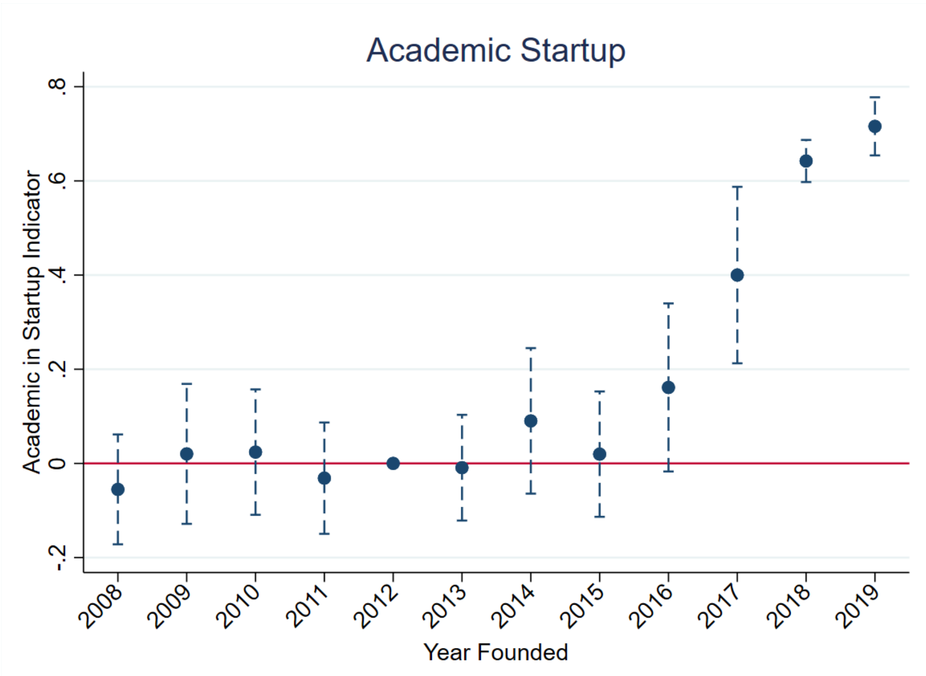

Figure 4. **Difference-in-difference estimates for Academic Startups: Neuro vs Other Healthcare**

The figure plots the coefficients for the estimation of dynamic version of Equation 1, with interaction terms of each founding year and the *Neuro* dummy where the dependent variable is an indicator variable for *Academic Startup*: startups who have a STEM academic in senior positions in the first three years after being founded. The unit of observation is an entrepreneurial firm. The 2012, i.e. t=(-1), interaction term is the excluded category, reported as zero in the figure. The vertical lines represent the 95% confidence interval for the coefficient estimates with robust standard errors.

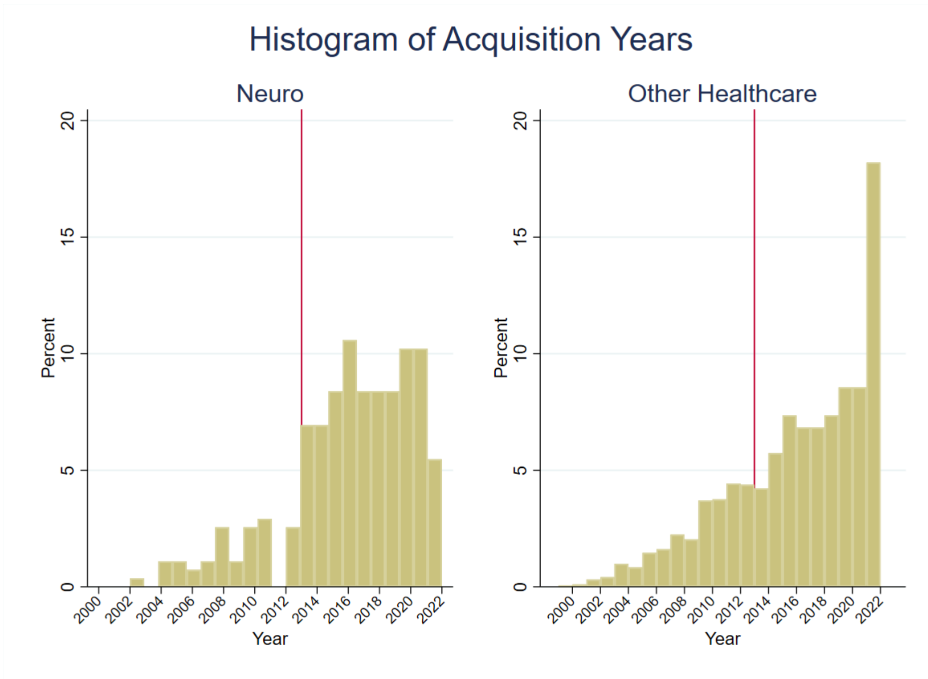

Figure 5. **Acquisitions of Neuro and other healthcare startups**

This figure plots a histogram of the year of acquisitions of neuro startups (left) compared to other startups in the healthcare sector (right).

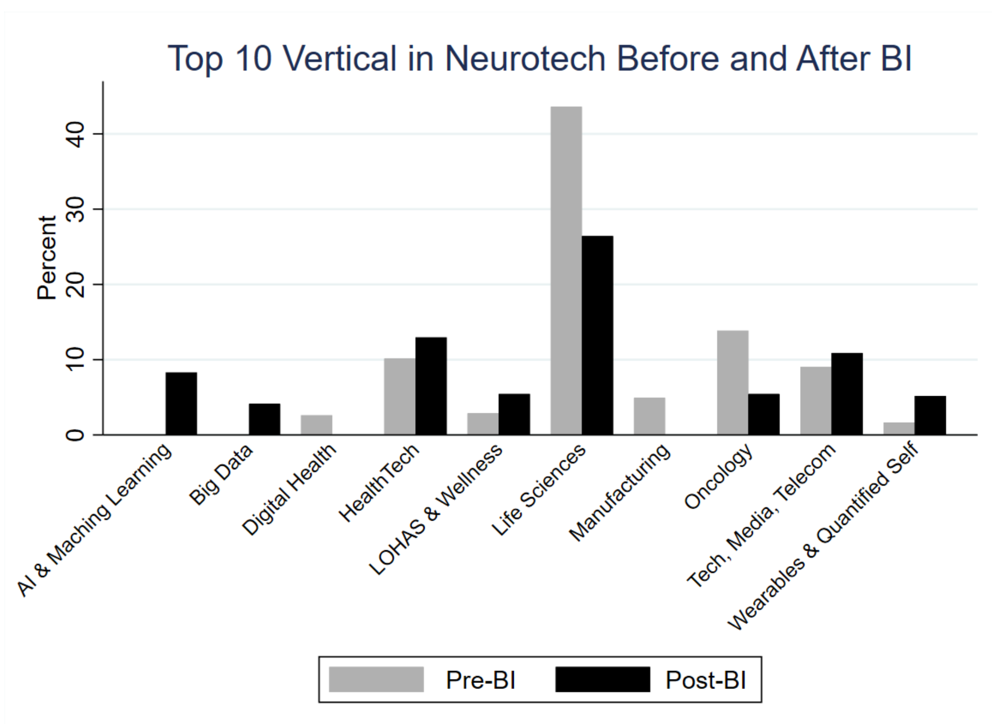

Figure 6. **Industry Verticals of Neuro Startups before and after the BI**

Table 1: Summary Statistics of Startups. This table shows summary statistics for 50,601 unique startups receiving VC financing between 2000 and 2019. Panel A presents financing information for all rounds where round size is not missing, while Panel B focuses on the financing information of the first round of finance with round size available. Panel C presents data at the startup level, including the number of patents, total financing rounds, and the number of founders with academic experience. Panel D offers summary statistics for the number of patents and the number of hired academic inventors, based on a startup and year panel dataset.

	N	Mean	St. Dev.	10%	50%	90%
Panel A: All Rounds						
Round Size	94,565	9.93	59.18	0.28	3.00	20.50
Pre-Money Valuation	51,157	80.51	953.54	2.75	12.60	100.00
Deal Year	94,565	2012.93	4.87	2006.00	2014.00	2019.00
Generating Revenue	94,544	0.56	0.50	0.00	0.00	1.00
#VCs	94,565	2.14	2.01	1.00	1.00	5.00
Round Number	94,565	2.22	1.63	1.00	2.00	4.00
Neuro Round==1	2,880	-	-	-	-	-
Panel B: 1st Round						
Round Size	42,520	4.57	18.40	0.15	1.60	9.55
Pre-Money Valuation	19,661	12.78	125.71	1.62	6.00	20.00
Generating Revenue	42,515	0.43	0.49	0.00	0.00	1.00
Deal Year	42,520	2012.64	5.05	2005.00	2014.00	2018.00
#VCs	42,520	1.77	1.65	1.00	1.00	4.00
Panel C: Startup Level						
Successful Exit	29,003	0.12	0.33	0.00	0.00	1.00
Exit Year	29,003	2016.24	4.16	2011	2017	2021
#Patents	44,417	2.85	27.58	0.00	0.00	4.00
#Academic Founders	44,417	0.16	0.50	0.00	0.00	1.00
Neuro Startup	836	-	-	-	-	-
Panel D: Startups-Year Level for startups with at least one patents						
#Academic Inventors	104,069	0.22	1.69	0.00	0.00	0.00
#Patents	104,069	0.91	3.48	0.00	0.00	2.00

Table 2: Funding Size. This table presents the results of OLS regressions estimating Equation 1. The dependent variable is the log of first round VC investment amount in Panel A and the log of pre-money valuation in Panel B for the first VC investment. The unit of observation is the first VC financing event of an entrepreneurial firm. The variable *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. # *Investors* counts the number of investors in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. Tables A6, A7, and A8 provide results for the sample including all financing rounds and explore alternative classifications of *Neuro* as robustness checks. The *t*-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(1st Investment Size $)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro×Post	0.495***	0.392***	0.309**	0.318***
	(5.07)	(3.58)	(2.14)	(3.17)
Neuro	0.079	0.119*	0.350***	0.029
	(1.26)	(1.80)	(3.40)	(0.44)
Ln(# Investors)	0.370***	0.545***	0.449***	0.433***
	(49.38)	(25.65)	(15.55)	(24.81)
Observations	39586	7995	4873	8564
Mean Outcome	0.579	0.858	0.727	0.937
Adj R-squared	0.173	0.203	0.140	0.175
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Panel B:	**Ln(Pre-Money Valuation $ in 1st Round)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro×Post	0.358***	0.410***	0.397**	0.228**
	(3.48)	(3.47)	(2.57)	(2.11)
Neuro	-0.006	-0.033	0.028	0.024
	(-0.09)	(-0.44)	(0.25)	(0.34)
Ln(# Investors)	0.187***	0.231***	0.206***	0.174***
	(21.97)	(11.27)	(7.65)	(9.48)
Observations	19599	4206	2506	5127
Mean Outcome	1.778	1.863	1.778	1.938
Adj R-squared	0.084	0.109	0.090	0.093
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Table 3: Financing of *Neuro Startups* as BI Employers. This table reports results of comparing round characteristics of *Neuro Startups*, if the startup has employed a BI scientist at the time of the round. The sample in limited only to *Neuro startups*. The dependent variable is the log of VC financing amount in Panel A, and log of Pre-Money Valuation in Panel B. A unit of observation is an entrepreneurial firm VC financing event. *BI˙Employer* is a dummy variable for rounds, where the startup has employed at least one BI scientist by the year of the round. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round FE* are dummies for the sequence of financing rounds. The *t*-statistics (in parentheses) are clustered at the startup level, with *** , ** and * representing significance at the 1%, 5% and 10% levels, respectively.

Panel A:	**Ln(round size $)**					
	All	Healthcare		All	Healthcare	
			[08-17]			[08-17]
	(1)	(2)	(3)	(4)	(5)	(6)
BI Employer×Post	0.538	0.530	0.525	0.497	0.525	0.606
	(2.505)**	(2.739)***	(1.890)*	(2.020)**	(2.101)**	(1.674)*
BI Employer	0.263	0.229	0.098	0.158	-0.022	0.226
	(1.859)*	(1.781)*	(0.572)	(0.660)	(-0.085)	(0.250)
Ln(# Investors)	0.920	0.945	0.904	0.754	0.768	0.587
	(22.172)***	(20.723)***	(12.832)***	(16.071)***	(15.163)***	(6.786)***
Observations	2,657	2,316	994	2,498	2,175	767
R-squared	0.390	0.360	0.344	0.712	0.694	0.714
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Firm FE	N	N	N	Y	Y	Y

Panel B:	**Ln(Valuation $)**					
	All	Healthcare		All	Healthcare	
			[08-17]			[08-17]
	(1)	(2)	(3)	(4)	(5)	(6)
BI Employer×Post	0.545	0.550	1.072	0.436	0.380	0.636
	(1.769)*	(2.264)**	(2.743)***	(1.269)	(1.125)	(1.386)
BI Employer	0.162	0.128	-0.111	0.329	0.105	-0.056
	(0.683)	(0.629)	(-0.463)	(1.076)	(0.320)	(-0.099)
Ln(# VCs)	0.492	0.491	0.309	0.585	0.633	0.559
	(47.905)***	(21.358)***	(9.267)***	(77.840)***	(46.965)***	(28.732)***
Observations	1,748	1,480	643	1,592	1,339	468
R-squared	0.534	0.463	0.490	0.857	0.828	0.902
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Firm FE	N	N	N	Y	Y	Y

Table 4: Success of the Exits. This table reports results from OLS regressions estimating Equation 1, where the dependent variable is an indicator variable for successful exits. A unit of observation is an entrepreneurial firm. *Successful Exit* is defined as an IPO or a M&A at a reported value at least twice the total capital invested. *(Time to Exit)* is the difference between the number of days between the first VC investment and the VC exit date. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for startups receiving the first VC financing event after the BRAIN Initiative (2013), where the year of the event itself has been excluded. *First VC Financing Year FE* (*Exit Year*) indicate dummies for financing (exit) year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

	Successful Exit				Ln(Time to Exit)			
	All	Patenting	Healthcare		All	Patenting	Healthcare	
				[08-17]				[08-17]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neuro×Post	0.128***	0.121***	0.087**	0.103**	-0.256***	-0.116*	-0.182***	-0.151**
	(3.22)	(3.13)	(2.20)	(2.17)	(-4.19)	(-1.91)	(-2.84)	(-2.11)
Neuro	0.071***	0.007	0.054**	0.042	0.216***	0.035	0.203***	0.164***
	(2.79)	(0.27)	(2.12)	(1.18)	(6.17)	(0.97)	(5.39)	(3.56)
Ln(Raised before exit)	0.065***	0.106***	0.100***	0.099***	0.078***	0.053***	0.046***	0.048***
	(56.44)	(36.90)	(38.48)	(31.17)	(42.83)	(13.83)	(11.12)	(10.33)
Observations	23097	4441	4598	2941	33609	6622	6157	3851
Mean Outcome	0.157	0.295	0.263	0.227	7.359	7.703	7.469	7.424
Adjusted R2	0.263	0.355	0.381	0.380	0.175	0.270	0.209	0.138
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
First VC Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Exit Year FE	Y	Y	Y	Y	N	N	N	N
State FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 5: Academic Startup. This table reports results from OLS regressions estimating Equation 1, where the dependent variable is an indicator variable for *Academic Startup*. *Academic Startup* are startups with at least one academic holding a senior position within the startup; see Section 3.5.1 for more details. A unit of observation is an entrepreneurial firm. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for startups receiving the first VC financing event after the BRAIN Initiative (2013), where the year of the event itself has been excluded. *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *Year FE* indicate dummies for financing year. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

Academdmic Startup Indicator				
	All	[08-17]	Healthcare	Patenting
	(1)	(2)	(3)	(4)
Neuro×Post	0.103	0.094	0.038	0.047
	(2.759)***	(2.141)**	(0.931)	(1.230)
Neuro	0.043	0.028	0.047	0.032
	(2.399)**	(0.951)	(2.597)***	(1.665)*
Observations	48,573	34,367	9,338	9,455
R-squared	0.074	0.080	0.069	0.070
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Table 6: Patents and Academic Inventors. This table presents regression results of Poisson estimations of Equation 3 using a firm-year panel dataset, which includes only patenting firms. The unit of observation is firm-year, spanning from the founding year to the first year of receiving VC funding for columns 1, 3, 5, and 7, and from the founding year to the year of VC exit for columns 2, 4, 6, and 8. The dependent variables in columns 1 and 2 are #*Patents* filed (and eventually granted) in year t. The dependent variables in columns 3 and 4 are #*Breakthrough patents* filed (and eventually granted) in year t. #*Breakthrough patents* are patents that received more citations than the citations at the 90 percentile within the same technology class and year. The dependent variables in columns 5 and 6 are the #*Academic Inventors* in the year t. In columns 7 and 8, the dependent variables are #*AI Patents* filed (and eventually granted) in year t. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. The *t*-statistics (in parentheses) are clustered at the startup level, with ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

	# Patents		# Breakthrough patents		# Academic Inventors		# AI Patents	
	<=1st Year		<=1st Year		<=1st Year		<=1st Year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neuro × Post	0.538	0.510	0.657	0.661	0.726	0.762	0.981	0.824
	(3.248)***	(4.481)***	(5.276)***	(5.751)***	(3.752)***	(3.606)***	(6.253)***	(3.178)***
Observations	80,564	105,675	35,862	51,188	29,758	42,409	28,309	40,525
Startup FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Appendix A: BRAIN Initiative Funding and Grants

In this section, we provide more details on the BRAIN Initiative's funding levels and organizational structure. The funding level for BRAIN was initially announced at $4.5 billion over a period of 12 years (NIH, 2014b). However, the exact funding levels and budget were updated annually. Six federal agencies were involved in the Initiative: NIH, NSF, DARPA, IARPA, FDA, and DoE. Although the FDA does not provide monetary funding, it supports the Initiative by enhancing the transparency and predictability of the regulatory landscape for neurological devices and assisting developers and innovators of medical devices. Given the variety of agencies funding the program, there is no single source reporting the overall funding amount. Therefore, we collect this information from three sources: 1) BI fact sheets, 2) agency budget reports, and 3) the sum of individual grants publicly available. The information from the last source is only available on the NIH and NSF websites; other agencies do not publicly report their funded projects and amounts. In cases of conflicting information from these three sources, we report the highest amount.

Figure A.2 presents the funding levels for NIH, NSF, DARPA, and other organizations. The *Other* category includes IARPA, DoE, and other non-profit organizations such as universities and private research institutes. The 2015 reported value for this category was budgeted to be spent over the following four years. Overall, NIH provides the largest amount of funding, with an investment of $3.1 billion. In the first four years of the program, DARPA is the second-largest funding agency. In 2018, five years after its announcement, the program underwent a review, leading to BRAIN 2.0, which included a revised version and updated scientific priorities. After 2018, there are no reports of DARPA and IARPA's involvement in the initiative, while NSF's funding level increased.

A.1. BI vs non-BI Grants in Neuroscience

In Table A2 Column (1), we provide total annual levels of funding for both BI and NIH non-BI Grants. To identify comparable Non-BI grants within the NIH, we applied three criteria: (1) the grants must contain *neuro keywords* in their project terms, (2) we exclude SBIR and STTR grants, and (3) they must be managed by the same NIH institutes and Centers that also are managing BI grants. These NIH institutes and Centers are NCCIH, NEI, NIA, NIAAA, NIBIB, NICHD, NIDA, NIDCD, NIMH, and NINDS. Before BI, there was previously funding available for neuroscience. From 2014 to 2022, NIH non-BI allocated $64 billion to neuroscience. On average, these non-BI grants received $0.47 million per project. For comparison, we obtained BI funding information from the BI website. The primary funding institutes of BI are NIH, NSF, and DARPA. NIH and NSF disclose their annual funding on their websites, while DARPA provided funding details only from 2014 to 2017. Therefore, the reported annual BI funding is based solely on available public information and may underestimate the actual figures. NIH typically contributed the most funding each year. BI grants are more competitive due to the significantly fewer BI projects. From 2014 to 2022, BI contributed an additional $5 billion, which represents 8% of the NIH non-BI grants. These BI grants, on average, received $1.10 million per project, which is more than double that of non-BI grants. Although BI grants do not significantly increase the total federal funding in neuroscience, they are highly competitive and offer larger average amounts per project. The significance of BI lies not in increasing funding but in its mission, such as mapping brain activity and integrating data science with neuroscience.

A.2. NIH vs NSF

We find 1,331 unique BI grants on the NIH site as of May 2023. We gathered detailed information on titles, keywords, start dates, end dates, Principal Investigators (PI), and amounts of BI grants for 1,195 grants using NIH RePORTER API, noting that 136 grants were unavailable. For these 1,195 BI grants, NIH provided 1.37 billion US dollars from 2014 to 2022, an average of 1.15 million per grant, and was awarded to 909 unique PIs across 218 unique institutions primarily located in the US. NIH BI grants mainly focus on research in neuroscience, biology, and medical science projects, as the majority amount was awarded to prestigious medical institutions and medical schools or universities. For example, the institutions that receive the largest and third largest amount of money are the Allen Institute and Salk Institute for Biological Studies, with $105,473,299 and $54,675,613, respectively. Both the Allen Institute and Salk Institute for Biological Studies are leading research institutes in neuroscience. Regarding the PIs of these grants, the top five PIs who receive the largest grants are biologists and neuroscientists.

Additionally, NSF matches the NIH in its financial contributions to research, having allocated $3.15 billion since 2014. NSF's funding spans a broader range of research disciplines. Notably, the top three PIs receiving the most funding are working in the different research disciplines. For example, Gregory Boebinger, a leader of the MagLab, received most NSF funds under BI. The MagLab is the premier global facility for magnet research, serving over 1,700 scientists yearly across various fields such as physics and bioengineering. Tomaso Poggio received the second-largest amount of money under BI from NSF. He is a computational neuroscience pioneer who conducts interdisciplinary research that connects brain sciences and computer science. The person ranked third is Arjun Yodh from the University of Pennsylvania's Department of Physics and Astronomy, who works across physics, medical physics, biophysics, and optical sciences. While NSF's funding amount is comparable to NIH's, it emphasizes a wider range of research disciplines. Thus, analyzing BI grants from both NIH and NSF offers a holistic view of the BI's funding landscape. Together, NIH and NSF have supported 2,428 research projects with a total expenditure of $4.38 billion since 2014, underscoring the comprehensive scope of BI funding.

Appendix B: Name-matching

In the person name-matching process, we first map the surnames between individuals using fuzzy matching and require the first three letters of surnames to be the same and allow for just one permissible spelling error because there are fewer variations in surnames. Subsequently, for each matched surname, we compare their first and middle names. For this purpose, we employ a fuzzy matching algorithm that is designed to recognize variables in first and middle names. The following variations of names are identified as the same names:

- "First name" + "middle name" matches to "First name" + "middle name initial" e.g., "Robert James" matches to "Robert J"
- "First name" + "two middle names" matches to "First name" + "middle name and middle name initial" e.g., "Robert James Waller" matches to "Robert James W" and "Robert JW"
- "First name" matches to known "Nicknames" associated with this given name, e.g., "Robert" matches to "Rob"

Appendix C: Analyzing the commercial and scientific impact of BI

The first two measures for commercial impact are constructed by Masclans et al. (2024) and Marx and Fuegi (2020, 2022). Their premise is that an academic output is more commercializable when it receives patent citations, indicating that the cited publication served as prior art for the patent. Marx and Fuegi (2020, 2022) provide data on such citations. For every publication, we count the number of patents that cite it. On average, BI publications receive 0.44 patent citations, compared to only 0.12 for other publications, with this difference being statistically significant at the 99% level.

We further test the difference in the number of citations for BI patents via a regression model in the Panel A of Table A3. Because most publications never receive a patent citation, we use a Poisson model to accommodate for an outcome variable with many zero values (Cohn et al., 2022). In Column (1), we regress the number of citations on a dummy variable for BI patents and include year fixed effects to capture time trends in citations. In Column (2), we repeat this exercise for a sub-sample of non-BI NIH-backed neuroscience papers. Across both specifications, we find a positive coefficient indicating the higher citations received by BI publications. Masclans et al. (2024) argue that patent citations reflect the ex post commercialization of an academic article but not its ex ante potential. They, therefore, develop a large language model (LLM) trained on a dataset of renewed patents— such patents are presumably more commercialized. This trained model is then used to generate two scores for each publications: commercial and scientific potential. We link these scores to the academic articles in our sample. In Column 3, we add the commercial and scientific potential scores as control variables. The coefficient on BI is still statistically significant, and indicates that BI publications are four times more likely to receive a citation from a patent compare to non-BI neuroscience. In Panel B, we directly compare the summary statistics on these scores across BI and non-BI neuroscience publications. The average commercial potential of non-BI grants after 2014 is 0.69, which is smaller than the commercial potential of BI publications at 0.78. The difference between the commercial potential of BI grants and non-BI grants is statistically significant at the 99% level, suggesting that research under BI grants is more commercializable than similar research grants in the sample period. .[39]

Table A3 Panel B shows basic summary statistics for the commercial potential of publications from BI grants with similar publications. Specifically, in Panel A of Table A3, we compare the commercial potential of BI output with the output of NIH-funded non-BI grants in neuroscience (Non-BI grants). We first investigate whether BI grants have a larger commercial potential than publications of Non-BI grants after 2014. Panel A of Table A3 shows that

For scientific impact, we rely on the number of citations an academic article receives from other articles. We find that BI-funded publications on average receive 16% higher citation from other academic articles compared to non-BI neuroscience, with the difference being statistically significant at the 1% level. In line with the Nature (2021) editorial article, this suggests that research grants under BI have indeed advanced basic neuroscience.

[39] We cannot perform a DiD analysis here because BI grants did not exist before 2014.

Appendix Figures and Tables

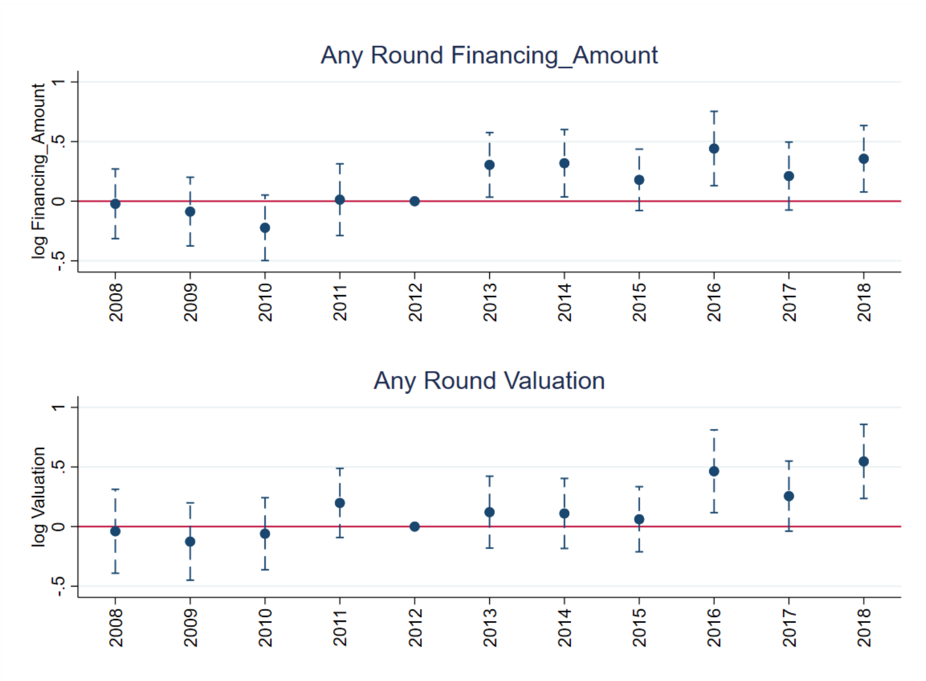

Figure A.1. **Difference-in-difference estimates for financing and valuation: Neuro vs Other Healthcare**

The figure plots the coefficients for the estimation of dynamic version of Equation 1, with interaction terms of each financing year and the *Neuro* dummy where the dependent variables are the log of the financing amount and the log of the pre-money valuation. These two figures include all rounds. The unit of observation is an entrepreneurial firm's first financing event. The 2012, i.e. t=(-1), interaction term is the excluded category, reported as zero in the figure. The vertical lines represent the 95% confidence interval for the coefficient estimates with robust standard errors.

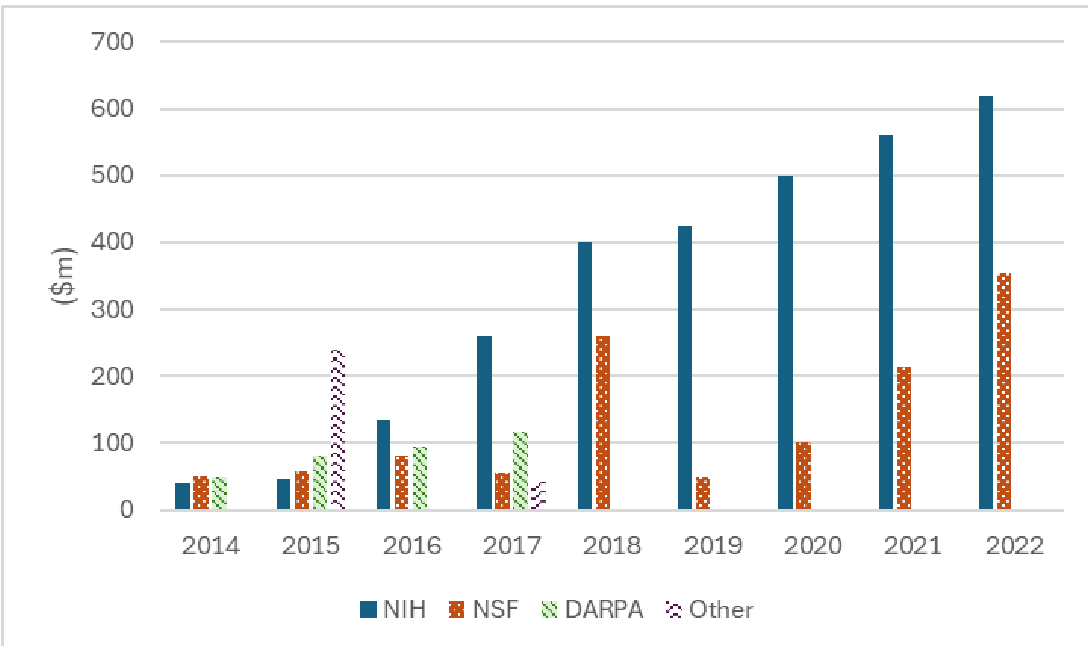

Figure A.2. **Total BRAIN Initiative Funding per Agency**

This Figure shows the total funding of the BRAIN Initiative (BI) by the funding organization. Except for NSF, 2014-2018 figures are collected from the BI factsheets and 2019-2022 from the NIH BI website. All NSF values report the total amount of the NSF BI grants.

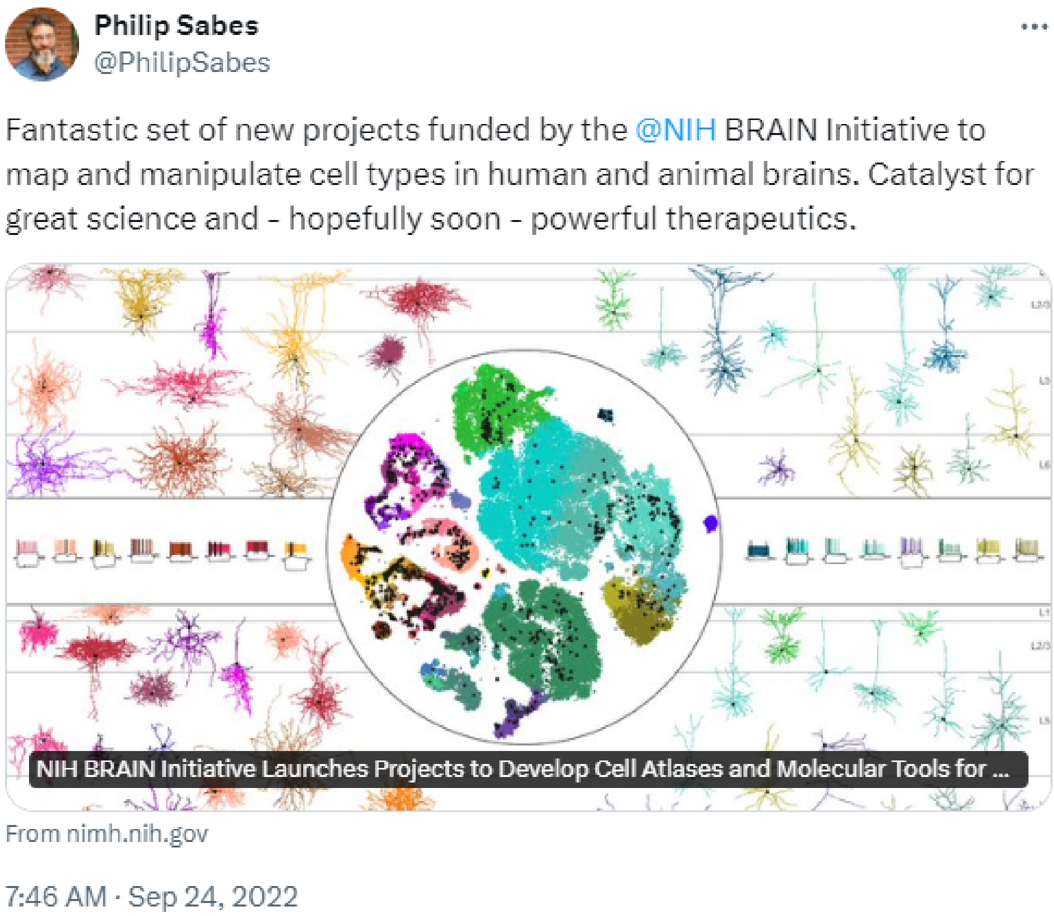

Figure A.3. **An Example of an Academic Co-founder**

This Figure shows a Tweet by Philip Sabes, one of the co-founders of Neuralink, a professor at UCSF, and a co-author under the BRAIN Initiative

Table A1: Variables Definitions

Variable name	Definitions	Tables
Independent variables		
Neuro	The indicator variable equals one if the startup is a *Nuero Startup*; zero otherwise. *Neuro Startup* is identified as startups granted at least one patent within neuroscience-related technology groups, as detailed in Section 3.3.	Table 2, 4, 5, 6,A9, A11,A12
Post	The indicator variable equals one for the years following the inception of the BRAIN Initiative (excluding 2013 as the year of the event); zero otherwise.	Table 2, 4,5, 6,A9, A11,A12
BI˙Employer	The indicator variable equals one if a *Neuro Startup* employs at least one BI scientist; zero otherwise. A BI scientist is an author of publications resulting from BI grants.	Table 3
Ln (# VCs)	The natural logarithm of the number of VCs in the round. Sources: PitchBook	Table 2, 3,A9,A11,A12
Ln(Raised before exit)	The natural logarithm of the total amount of financing that the startup has raised before the exit of VC. Sources: PitchBook	Table 4
Ln(Total $ Raised)	The natural logarithm of the total amount of financing that the startup has raised up to the year. Sources: PitchBook. Sources: PitchBook	Table 6
Dependent Variables		
Ln(round size$)	The natural logarithm of VC financing amount. Sources: PitchBook	Table 2,3, A11
Ln(Pre-Money Valuation$)	The natural logarithm of VC Pre-Money Valuation. Sources: PitchBook	Table 3,A12
Successful Exit	The indicator variable equals one for startups' successful exit. A successful exit is an IPO or a M&A at a reported value at least twice the total capital invested. Sources: PitchBook	Table 4
Academic Founder Dummy	The indicator variable equals one for startups founded by at least one Academic Founder; zero otherwise. An Academic Founder is defined as a scientist who either launches a startup within five years of departing academia or who simultaneously engages in academic work while establishing startups.	Table 5
#Patents	Startup i's the total number of patents filed (and eventually granted) in year t	Table 6
#Breakthrough Patents	Startup i's the number of breakthrough patents filed (and eventually granted) for the next n years. The breakthrough patents at the 90 percentile are patents that received more citations than the citations at the 90 percentile within the same technology class and year.	Table 6
Avg. Adjusted Cites	Startup i's the average adjusted cites of patents filed (and eventually granted) in year t. The adjusted cites are the number of cites over the average cites of patents in the same technology field and granted year.	Table 6
#Academic inventors hired	The number of Academic inventors hired by the startup at year t. Academic inventors are inventors who begin working in startups following their academic roles or upon finishing their doctoral degrees.	Table 6
Generating Revenue Dummy	The indicator variable equals one for startup is generating revenue; zero otherwise.	Table A9

Table A2: BI grants vs. Non-BI grants This table compares neuroscience funding under the BRAIN Initiative with NIH non-BI funding for the field. All monetary amounts are shown in \$ million. Columns (1) shows *Total Funding* as the total budget allocated to BI. Column (2) shows the sum of comparable Non-BI grants per fiscal year. *Average Amount per Project* is calculated by dividing the *Awarded Amount* by the number of Projects per agency.

	Total Funding (\$m)		Average Amount per Project (\$m)			Diffs	
FY	BI	NIH non-BI	NIH BI	NSF BI	NIH Non-BI	(3)-(5)	(4)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000		1,251					
2001		1,469					
2002		1,711					
2003		1,902					
2004		2,076					
2005		2,136					
2006		2,124					
2007		3,529					
2008		3,706					
2009		4,552					
2010		4,586					
2011		4,129					
2012		4,351					
2013		4,205					
2014	142	4,513	0.8	0.37	0.38	0.42***	0
2015	425	4,618	0.57	0.44	0.39	0.18***	0.05
2016	312	5,921	0.65	0.65	0.42	0.23***	0.23***
2017	651	6,489	1.47	0.49	0.45	1.03***	0.04
2018	649	7,239	0.89	2.4	0.47	0.42***	1.93***
2019	472	8,249	1.07	0.63	0.5	0.57***	0.13
2020	600	8,658	1.22	0.75	0.53	0.69***	0.22***
2021	775	8,996	1.27	1.73	0.56	0.71***	1.17***
2022	974	9,450	1.66	2.79	0.57	1.09***	2.22***
Total Amount	5,001	64,132					

Table A3: Commercial Potential of BI research This table compares the commercial potential of BI research against research from non-BI neuroscience grants. Panel A presents the results of the Poisson publication of the *#Patent Citations* received by publications on the BI grant indicator. A unit of observation is a publication. The key dependent variable, *#Patent Citations*, represents the number of patent citations each publication receives. The BI indicator variable equals one for publications resulting from BI grants and zero otherwise. Control variables include *Non-BI Neuro*, an indicator for publications from NIH-funded non-BI neuroscience grants, as well as measures of commercial and scientific potential. All regressions include year-fixed effects. Columns 1 and 3 report regression results for the full sample, while Column 2 focuses specifically on publications from NIH-funded grants in neuroscience. Panel B utilizes the predicted ex-ante commercial potential of publications from Masclans et al. (2024). Group A in Panel B comprises publications from BI grants, whereas Group B includes all publications from non-BI neuroscience grants after 2014. Column 3 presents the difference between Groups A and B and reports the statistical significance of the t-test for mean differences and the Wilcoxon rank-sum test for median differences.

Panel A: Patent Citations of Publications

	(1)	(2) Neuroscience Pubs	(3)
	#Patent Citations	#Patent Citations	#Patent Citations
BI	2.022	1.192	1.485
	(0.301)***	(0.307)***	(0.301)***
Non-BI Neuro			0.428
			(0.056)***
Commercial Potential			4.361
			(0.065)***
Scientific Potential			0.383
			(0.052)***
Constant	-1.761	-1.203	-5.047
	(0.009)***	(0.053)***	(0.061)***
Observations	2,274,602	83,838	2,274,602
Year FE	Y	Y	Y

Panel B: Predicted Commercial Potential of Publications

	BI (A)	Non-BI Neuroscience post 2014 (B)	(A-B)
Mean	0.78	0.69	0.09***
Median	0.84	0.78	0.06***
SD	0.17	0.26	

Table A4: Model performance This table presents the performance metrics from 2015 to 2020 for models we trained. These performance matrices are generated using the testing dataset not used in the training process. We present each model's recession, recall, and F1-score for each class, and the aggregated measure across classes contains the macro average and weighted average. Macro average calculates the metric independently for each class and then takes the average. Weighted average calculates the metric for each class and weights it by the number of observations in that class.

2015

	Precision	Recall	F1-Score	Support
0	0.90	0.96	0.93	28
1	0.97	0.90	0.93	31
Maro avg	0.93	0.93	0.93	59
Weighted avg	0.93	0.93	0.93	59

2016

	Precision	Recall	F1-Score	Support
0	0.92	0.90	0.91	81
1	0.89	0.92	0.91	74
Maro avg	0.91	0.91	0.91	155
Weighted avg	0.91	0.91	0.91	155

2017

	Precision	Recall	F1-Score	Support
0	0.92	0.91	0.92	166
1	0.89	0.90	0.89	130
Maro avg	0.90	0.90	0.90	296
Weighted avg	0.91	0.91	0.91	296

2018

	Precision	Recall	F1-Score	Support
0	0.96	0.90	0.93	268
1	0.89	0.95	0.92	241
Maro avg	0.93	0.93	0.93	509
Weighted avg	0.93	0.93	0.93	509

2019

	Precision	Recall	F1-Score	Support
0	0.90	0.92	0.91	373
1	0.93	0.91	0.92	409
Maro avg	0.92	0.92	0.92	782
Weighted avg	0.92	0.92	0.92	782

2020

	Precision	Recall	F1-Score	Support
0	0.92	0.96	0.94	559
1	0.95	0.92	0.94	551
Maro avg	0.94	0.94	0.94	1110
Weighted avg	0.94	0.94	0.94	1110

Table A5: Pre-treatment trend This table repeats Equation 1 to investigate if the Pre-trend starts before event years (2013) and uses all years before 2013 as the placebo treatment year. For example, column 1 estimates the Equation 1 using the sample before 2008, and the placebo treatment year is 2008. The dependent variable in Columns 1 to 5 is the logarithm of deal size for the first round. The dependent variable in Columns 6 to 10 is the logarithm of deal size for all rounds.

	Deal Size									
	First Round					All Rounds				
Period=t¡=T	T=2008	T=2009	T=2010	T=2011	T=2012	T=2008	T=2009	T=2010	T=2011	T=2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Neuro×Post(=T)	0.202	0.019	-0.250	0.053	0.328	-0.117	0.029	-0.252	0.095	0.205
	(0.759)	(0.070)	(-1.069)	(0.222)	(1.234)	(-0.815)	(0.217)	(-1.877)*	(0.734)	(1.558)
Neuro	0.055	0.051	0.029	-0.005	0.022	0.221	0.169	0.162	0.111	0.130
	(0.475)	(0.475)	(0.295)	(-0.056)	(0.252)	(2.648)***	(2.199)**	(2.301)**	(1.700)*	(2.067)**
Ln(# VCs)	1.041	1.057	1.056	1.022	1.015	0.976	0.996	1.011	1.006	1.008
	(14.620)***	(15.901)***	(16.703)***	(16.646)***	(17.393)***	(22.236)***	(25.038)***	(27.442)***	(29.311)***	(31.652)***
Observations	1,089	1,258	1,433	1,653	1,869	2,509	3,032	3,612	4,284	4,972
R-squared	0.203	0.213	0.209	0.210	0.208	0.333	0.345	0.336	0.337	0.336
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A6: Funding Size. This table presents the results of OLS regressions estimating Equation 1. The dependent variable is the log of VC investment amount in Panel A and the log of pre-money valuation in Panel B. A unit of observation is an entrepreneurial firm VC financing event. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round FE* are dummies for the sequence of financing rounds. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(Round Size $ for All Rounds)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro×Post	0.287***	0.221***	0.225***	0.147**
	(4.29)	(3.28)	(2.97)	(2.22)
Neuro	0.101**	0.113**	0.168***	0.107**
	(1.97)	(2.15)	(2.61)	(2.09)
Ln(# Investors)	0.613***	0.763***	0.683***	0.711***
	(107.18)	(60.01)	(39.69)	(67.16)
Observations	106576	23737	12567	31194
Mean Outcome	1.285	1.491	1.255	1.725
Adj R-squared	0.365	0.371	0.330	0.384
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y
Panel B:	**Ln(Pre-Money Valuation $ for All Rounds)**			
	All	Healthcare		Patenting
			[08-17]	
	(5)	(6)	(7)	(8)
Neuro×Post	0.241***	0.239***	0.202**	0.106
	(2.74)	(2.76)	(2.29)	(1.21)
Neuro	0.132**	0.052	0.126	0.193***
	(2.06)	(0.79)	(1.62)	(3.00)
Ln(# Investors)	0.340***	0.306***	0.235***	0.382***
	(46.81)	(21.10)	(12.14)	(28.11)
Observations	60739	13612	7126	20218
Mean Outcome	2.918	2.957	2.718	3.265
Adj R-squared	0.491	0.462	0.432	0.500
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y

Table A7: Funding Size. This table presents the results of OLS regressions estimating Equation 1. The dependent variable is the log of VC investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is the first VC financing event of an entrepreneurial firm, and only the first rounds are included in this table. The variable *Neuro (Def 2)* is a dummy variable for a neurotech startup; a neurotech startup is a firm that files for a neuro patent within the first five years after its founding. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. The *t*-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(1st Round Size $)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro(Def 2)×Post	0.426***	0.311**	0.350**	0.243**
	(3.85)	(2.54)	(2.23)	(2.14)
Neuro(Def 2)	0.138*	0.147*	0.131	0.076
	(1.82)	(1.87)	(1.11)	(0.97)
Ln(# Investors)	0.369***	0.544***	0.456***	0.432***
	(49.33)	(25.57)	(16.39)	(24.73)
Observations	39586	7995	4872	8564
Mean Outcome	0.579	0.858	0.727	0.937
Adj R-squared	0.173	0.202	0.177	0.175
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Panel B:	**Ln(Pre-Money Valuation $ in 1st Round)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro(Def 2)×Post	0.361***	0.378***	0.500***	0.210*
	(3.40)	(3.21)	(3.42)	(1.89)
Neuro(Def 2)	-0.058	-0.081	-0.186*	-0.021
	(-0.76)	(-1.01)	(-1.70)	(-0.27)
Ln(# Investors)	0.187***	0.232***	0.200***	0.174***
	(21.97)	(11.26)	(7.58)	(9.47)
Observations	19599	4206	2505	5127
Mean Outcome	1.778	1.863	1.778	1.938
Adj R-squared	0.083	0.107	0.114	0.092
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Table A8: Funding Size. This table presents the results of OLS regressions estimating Equation 1. The dependent variable is the log of VC investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is the first VC financing event of an entrepreneurial firm, and only the first rounds are included in this table. The variable *Neuro (Def 3)* is a dummy variable for a neurotech startup; the neurotech startup is defined as a startup's business description contains one of our *Neuro keywords*: {*neuro, nerve, brain, optogenetic, Parkinson, Alzheimer, and dementia*}. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. # *VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. The *t*-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(1st Round Size $)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro(Def 3)×Post	0.253***	0.211**	-0.009	0.273**
	(2.82)	(2.16)	(-0.07)	(2.21)
Neuro(Def 3)	-0.155**	-0.106	0.022	-0.226***
	(-2.22)	(-1.46)	(0.21)	(-2.61)
Ln(# Investors)	0.370***	0.548***	0.460***	0.433***
	(49.45)	(25.77)	(16.51)	(24.82)
Observations	39586	7995	4872	8564
Mean Outcome	0.579	0.858	0.727	0.937
Adj R-squared	0.172	0.200	0.173	0.174
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Panel B:	**Ln(Pre-Money Valuation $ in 1st Round)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro(Def 3)×Post	0.233**	0.236**	0.301**	0.349**
	(2.27)	(2.09)	(1.99)	(2.42)
Neuro(Def 3)	-0.091	-0.078	-0.169	-0.151
	(-1.11)	(-0.90)	(-1.41)	(-1.44)
Ln(# Investors)	0.188***	0.232***	0.200***	0.174***
	(21.99)	(11.29)	(7.55)	(9.49)
Observations	19599	4206	2505	5127
Mean Outcome	1.778	1.863	1.778	1.938
Adj R-squared	0.083	0.106	0.111	0.093
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Table A9: Startups' Revenue Status. This table reports results from OLS regressions estimating Equation 1, where the dependent variable is a dummy variable for whether the startup is generating revenue. A unit of observation is an entrepreneurial firm VC financing event. In Panel A, only the first rounds are included, and in Panel B, all rounds are included. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round FE* are dummies for the sequence of financing rounds. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 1st Rounds	**Generating Revenue Dummy**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	-0.164	-0.148	-0.109	-0.098
	(-4.628)***	(-4.015)***	(-2.040)**	(-2.318)**
Neuro	0.076	0.033	0.005	-0.002
	(3.742)***	(1.533)	(0.134)	(-0.080)
Ln(# VCs)	0.022	-0.013	-0.030	-0.012
	(5.520)***	(-1.534)	(-2.248)**	(-0.784)
Observations	42,488	9,363	4,378	3,453
Adj R-squared	0.134	0.104	0.037	0.069
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Panel B: All Rounds	**Generating Revenue Dummy**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	-0.168	-0.138	-0.100	-0.081
	(-6.818)***	(-5.441)***	(-3.367)***	(-2.747)***
Neuro	0.054	0.033	0.021	-0.008
	(2.782)***	(1.581)	(0.767)	(-0.360)
Ln(# VCs)	0.011	-0.009	-0.029	-0.000
	(4.087)***	(-1.830)*	(-3.995)***	(-0.021)
Observations	94,506	29,039	14,060	10,666
Adj R-squared	0.179	0.174	0.126	0.138
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y

Table A10: Sector Distribution of Acquirers in Healthcare Startups. This table categorizes acquirers into sectors, comparing their engagement with neuro and other healthcare startups, pre- and post-BI.

	Neuro				Other Healthcare			
	Pre-BI		Post-BI		Pre-BI		Post-BI	
	#	%	#	%	#	%	#	%
Healthcare	30	93.75%	142	89.31%	740	87.89%	861	86.97%
IT	2	6.25%	7	4.40%	47	5.58%	55	5.56%
B2B			6	3.77%	25	2.97%	31	3.13%
B2C			4	2.52%	12	1.43%	28	2.83%
Finance					11	1.31%	10	1.01%
Materials					5	0.59%	5	0.51%
Energy					2	0.24%		
Total	32		159		840		990	

Table A11: Funding Size without AI and Big Data Startups. This table repeats the exercise in Table 2, while excluding startups in AI or Big Data verticals. A unit of observation is an entrepreneurial firm VC financing event. In Panel A, only first rounds are included and in Panel B all rounds are included. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round FE* are dummies for the sequence of financing rounds. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

Panel A: 1st Rounds	**Ln(round size $)**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.647	0.421	0.387	0.253
	(6.006)***	(3.783)***	(2.390)**	(1.986)**
Neuro	0.042	-0.017	0.047	0.042
	(0.614)	(-0.242)	(0.363)	(0.534)
Ln(# VCs)	0.754	0.755	0.589	0.882
	(62.653)***	(29.070)***	(14.625)***	(20.269)***
Observations	34,790	7,720	3,190	3,076
Adj R-squared	0.202	0.192	0.161	0.221
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Panel B: All Rounds	**Ln(round size $)**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.344	0.185	0.212	0.125
	(4.534)***	(2.430)**	(2.130)**	(1.834)*
Neuro	0.092	0.093	0.088	0.178
	(1.694)*	(1.680)*	(1.102)	(4.003)***
Ln(# VCs)	0.855	0.878	0.861	1.031
	(100.001)***	(59.320)***	(40.618)***	(52.306)***
Observations	77,687	23,990	10,575	9,488
Adj R-squared	0.334	0.338	0.343	0.286
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y

Table A12: Valuations without AI and Big Data Startups. This table repeats the exercise in Table 2, while excluding startups in AI or Big Data verticals. A unit of observation is an entrepreneurial firm VC financing event. In Panel A, only first rounds are included and in Panel B all rounds are included. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round FE* are dummies for the sequence of financing rounds. The *t*-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with *** , ** and * representing significance at the 1%, 5% and 10% levels, respectively.

Panel A: 1st Rounds	**Ln(Pre-Money Valuation $)**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.375	0.219	0.377	0.231
	(3.514)***	(1.953)*	(2.270)**	(1.840)*
Neuro	-0.031	0.007	-0.073	-0.003
	(-0.467)	(0.098)	(-0.604)	(-0.035)
Ln(# VCs)	0.299	0.259	0.255	0.309
	(24.295)***	(10.097)***	(6.684)***	(7.874)***
Observations	15,752	4,283	1,821	1,724
Adj R-squared	0.089	0.079	0.072	0.103
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Panel B: All Rounds	**Ln(Pre-Money Valuation $)**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.216	0.065	0.103	0.220
	(2.601)***	(0.772)	(1.040)	(2.697)***
Neuro	0.123	0.184	0.209	0.215
	(2.070)**	(2.979)***	(2.657)***	(3.955)***
Ln(# VCs)	0.391	0.399	0.398	0.487
	(38.282)***	(22.506)***	(16.333)***	(20.568)***
Observations	41,127	14,821	6,761	5,725
Adj R-squared	0.438	0.454	0.455	0.158
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y