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 risk. 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 risk: 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 requires 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 marked by asymmetric information, long timelines, and thus high uncertainty. The lack of appropriation and increasing returns in use stem from the non-excludable nature of scientific knowledge. Basic science generates spillovers that are beneficial for society at large but cannot be fully approporiated by the original investor.[1] These features impair 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 a *public good* to the market to commercialize.

Venture capital (VC) investments seem to reflect these ideas. While VC is a major market mechanism in financing innovation (Howell, Lerner, Nanda, and Townsend, 2020), there are concerns over VC funds' increasing focus on software startups to the detriment of nascent technologies building on new science, known as *deep tech*. These technologies are crucial for addressing significant societal challenges, such as climate change and Alzheimer's disease. 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. In line with Nelson and Arrow's arguments, high technical risk is among the reasons suggested for this decline. Lerner and Nanda (2020) and Dalla Fontana and Nanda (2023) argue that these ventures are incompatible with the VC model. The typical VC model is characterized by staged financing and funds with a finite life of 10-12 years. These features suit projects that allow cheaper experimentation and rapid learning about the project's viability in the early stage. The software sector aligns well with the VC criteria due to the decline in the cost of experimentation arising from technical advances such as cloud computing (Ewens, Nanda, and Rhodes-Kropf, 2018). In contrast, commercializing emerging technologies requires longer timelines and higher upfront R&D costs, implying high technical risk. Such risk also deters potential entrepreneurs—typically academic scientists with risk-free salaried jobs who face a high opportunity cost of undertaking the non-diversifiable risk of entrepreneurship (Hall and Woodward, 2010).

Interestingly, the early stages of the IT sector, the realm of venture capital, highlights the role of government in reducing the technical risk. The internet and many related VC-backed

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

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

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. Andressen 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.[3] Andreessen later remarked that *"if it had been left to private industry, it wouldn't have happened ... at least, not until years later."*[4]

Nonetheless, the effect of public funding on the investment behaviour of venture capitalists (VCs) in basic science is far from clear. On the one hand, public funding could be allocated inefficiently, with no real positive impact on the underlying science.[5] Public funding could even crowd out private investments by subsidizing R&D for entrepreneurs, thus reducing their need for costly dilutive VC financing.[6] On the other hand, large-scale, coordinated government investments in producing basic science can reduce the technical risk and crowd in private investments. We empirically test these views in the VC setting and ask: first, does large mission-oriented public funding aimed at filling the gaps in basic science foster VC investments? Second, and perhaps more importantly, through what channels can public funding spur venture capital?

Studying these questions requires a significant exogenous increase in government funding of basic science in one area. Importantly, the shock must be orthogonal to the scientific advances or market dynamics. We believe that the BRAIN Initiative possess 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. The innovation literature underscores the

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

[4] Perine (2000)

[5] Such distortions might arise because politicians may direct subsidies to benefit themselves (Lerner, 2009).

[6] For example, Hellmann, Schure, and Vo (2021) document a substitution effect between VC and angel investments. Also, due to the VCs' practice of aggressively diluting earlier shareholders, some angel investors only invest where managements promise never to seek out venture capital (Holstein, 2012).

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. Another example of a *Grand Challenge* is the Human Genome Project (HGP), which aimed to determine the complete sequence of DNA bases in the human genome. The HGP spurred the creation of genomics markets. Battelle Institute (2011) estimates that for every federal dollar invested in the HGP, $141 has been generated in the economy. The HGP has been a role model for the BRAIN Initiative (BI), and its success has significantly influenced the design of the BRAIN Initiative.

Similar to HGP, BI has a mission: to produce a map of the human brain. Before the BI, progress in neuroscience mainly involved understanding the micro-scale functions of the brain and single neurons. The field lacked an understanding of the macro-level activity of neural circuits. Through two influential papers, leading neuroscientists proposed a large-scale effort, called Brain Activity Map, to fill this gap.[7] This foundational knowledge is not only the building block for understanding brain and neurological disorders (e.g., Alzheimer's, Parkinson's, epilepsy) but it also directly contributes to wider technological areas—e.g., medical devices, prosthetics with sensory feedback, brain-computer interface, and cognitive computing (The White House, 2013; NIH, 2014a). The multidisciplinary contributions of BI are reflected in various government agencies that fund the program: NIH (health), NSF (science), FDA (food and drugs), IARPA (intelligence), DARPA (defence), DoE (energy). We estimate that this group, named the BRAIN Initiative Alliance, has spent over $5B in funding BI between 2014 and 2022. The program is set to run until 2026.

A possible concern with using this shock is that the underlying premise of neurotechnologies would have attracted investors, particularly VCs, independent of this government program. While we recognize the commercial potential of neurotechnologies, it is unlikely that VC funds, with the average fund sizes of $145m,[8] would have invested an amount comparable to the BI. Even large pharmaceutical companies were cutting their neuroscience R&D expenditures in the years leading up to the BI due to the high risk and failure rates in the field.[9] Still, the government's funding could reflect other unobservable advances in the field. In contrast, our dynamic estimations do not show evidence of a pre-trend or elevated VC activity in neuro space prior to 2013. Furthermore, BI was designated as a *Grand Challenge*

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

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

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

from a diverse menu of 12 other scientific projects (Sejnowski, 2014), highlighting a degree of randomization. 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. Using three separate measures of commercial viability, we find this to be the case. 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 a patent than similar publications. We obtain similar results using data from Masclans, Hasan, and Cohen (2024), who predict the commercial potential of a publication – i.e., the ex-ante likelihood of receiving patent citations.

Nonetheless, we believe 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. Additionally, patents must cite prior art immediately related to the invention rather than the broader scientific foundation on which the invention is based.[10] To overcome these limitations, we employ a large language model (LLM) to identify patents influenced by BI research output. Inspired by the methodologies used in Masclans et al. (2024) and Giczy, Pairolero, and Toole (2022), we fine-tune a SciBERT model[11] using the labeled sample that includes positive cases, the abstracts of patents that cite BI research outputs,[12] and negative cases, patents randomly selected from filings before the BI. The model estimates that knowledge of BI has influenced 67% of all neuroscience-related patents with significant spillovers in other fields.

To study the effect of BI, we construct a comprehensive dataset with information on startup financing, innovation, and employees. We compile a sample of US VC-backed startups receiving their first VC funding round between 2000-2019 using PitchBook. 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. To examine the direct impact of the BI, we collect data on grants, including the dollar amount, output pub-

[10]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.

[11]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).

[12]Most patents citing BI are associated with academic institutions.

lications, 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 larger investments from the VCs post-BI compared to various startup control groups. Such investments are also made at higher company valuations. These results suggest that the BI made neurotechnology more *investable*[13] for VCs. If public funding reduces the technical risk of neuro startups, this is likely to be reflected when VCs invest in the company for the first time. In the first VC round, the risk is more skewed towards technological feasibility rather than product performance or market validation. We find our results are consistent across the first rounds, indicating reduced technical risk. The reduced technical risk is also reflected in VCs' successful exits from their neuro investments through IPOs or acquisitions;[14] this illustrates that the broader market also recognizes the value of these firms. Our control groups include all VC-backed startups, those with a patent,[15] 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, 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. [16] 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

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

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

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

[16]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 academic entrepreneurship drops.

such scientist, Philip Sabes, a professor of neuroscience at UCSF.[17]

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). Decoding this complex network demands substantial computing capacity, a key focus of the BI. The initiative has strengthened the intersection between neuroscience and data science by enhancing computational infrastructure, mandating data sharing, and directly funding AI-related research (Zador, Escola, Richards, et al., 2023). For instance, Google Research has collaborated closely with BI scientists to develop computational tools for managing one of the BI datasets, which is sized at 25K terabytes (Januszewski, 2023). We find that NIH's BI grants are three times more likely to fund data science-related areas compared to conventional NIH neuroscience grants. 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."* Furthermore, BI emphasizes interdisciplinary research between neuroscientists, engineers, statisticians, chemists, and data scientists. A comparison of the underlying technological areas that neuroscience companies are active in shows that after the BI, the area becomes broader than life sciences and encompasses areas such as AI and machine learning, big data, and brain-computer interface. 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, the acquirers were almost entirely in the healthcare sector, while after the BI, acquirers themselves belong to a broader range of sectors, including IT, B2B, and B2C.

The adaptability of neuroscience to AI raises an omitted variable concern, whereby VCs finance *Neuro startups* more favorably not because of the positive effects of BI, but because neuroscience is a fertile ground for applications of AI. While our results are robust to the

[17] Elon Musk is another co-founder of this company, along with six others.

exclusion of *Neuro startups* that employ AI and big data technologies, we further provide direct evidence on the treatment effects of BI. Arora, Belenzon, Cioaca, Sheer, and Zhang (2023) argue that university innovation, embodied in human capital trained in universities, is an efficient approach to fostering corporate innovation. Inspired by this, we focus on the human capital that benefits from the BI grants, 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. We link these publications to Scopus and identify the co-authors of these papers, whom we call *BI scientists*. The underlying assumption is that the knowledge generated by BI is reflected in the co-authors of these papers. For every *Neuro startup*, we identify the first financing round, when a BI scientist is hired. This round is classified as the point when a startup is considered treated. Compared to other non-treated *Neuro startups*, BI-employers raise more money from VCs, highlighting the value VCs place on the technical knowledge of scientists exposed to 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. Colonnelli, Li, and Liu (2024) run a field experiment on VC and PE funds in China and find that fund managers dislike investing with the government as a partner. Fleming, Greene, Li, Marx, and Yao (2019) show US corporations and startups increasingly rely on government-backed innovation. Bai, Bernstein, Dev, and Lerner (2021) show that government and private market co-investments can be 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) finds SBIR funding plays a certification role by conveying information about a startup's quality to investors. Howell (2017), on the other hand, finds initial Phase I SBIR funding enables startups to prove the viability of their project to investors. 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) find 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 filling the gaps in basic science. Such funding creates a public good that has yet to spill over into the commercialization and entrepreneurial processes. These spillover effects 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.[18] 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. Our work emphasizes the crucial role of public funding in facilitating private market engagement by advancing basic science and supplying entrepreneurial talent.

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).[19] Up to that point, to understand neural activity, neuroscientists were using electrodes that sparsely sample brain activity, typically capturing signals from one to a few neurons in a specific region. However, the article argues that since neural circuits may consist of millions of neurons, it is likely that the functioning of neuronal ensembles occurs at a multi-neuronal level, which cannot be observed through single-neuron recordings – 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 as follows:

> *"Emergent-level problems are not unique to neuroscience. Breakthroughs in understanding complex systems in other fields have come from shifting the focus*

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

[19] 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.

> *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[20] 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. Additionally, the process leading to the BRAIN Initiative's designation as a Grand Challenge in the US was more transparent than its European counterpart. BI's organizational structure was notably more decentralized, involving multiple agencies such as the NIH, NSF, DARPA, IARPA, and FDA, each supporting their specific projects of interest, whereas a single central selection committee guided the HBP. 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 BRAIN Initiative, which is set to end in 2026, has already been applauded by the neuroscience community (Nature, 2021).

In 2014, the funding level for the BRAIN Initiative was initially 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 BRAIN Initiative Alliance–a consortium of federal agencies

[20] Alivisatos et al. (2013)

funding the BI–has invested over \$5 billion in basic neuroscience research between 2014 and 2022.[21] Details on annual funding levels by the agency are provided in Appendix A. While on the surface, the \$5B BI investment represents 10% of NIH's overall expenditure on neuroscience, it is important to recognize the breadth of neuroscience and the position of BI in it. In colloquial circles, BI has been compared with the space program and referred to as the "*moonshot between our ears*." This is because BI directs funds to a critical, lesser-understood area of neuroscience: mapping brain activity. This effort aims to enhance our understanding of the inner workings of the brain and address technical challenges (Mott, Gordon, and Koroshetz, 2018; Nature, 2021).

In Section 3.4, we compare NIH's non-BI grants in neuroscience to BI grants, finding that BI grants receive 16% more citations, indicative of greater scientific impact. Notably, one of the sub-projects within the BRAIN Initiative, the Cell Census Network, aims to identify and catalog 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.

Furthermore, the BI has significantly strengthened the interface between neuroscience and data science, particularly by facilitating data sharing and directly funding AI-related research. 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."* This is manifested in the BI's open-source data-sharing policy, which mandates awardees to disseminate their data on designated BI data archives, thereby reducing research barriers and promoting knowledge spillover (National Institutes of Health (NIH), 2019) within the neuroscience community and outside.

While the data-sharing requirements of BI also made neuroscience research a fertile ground for applying AI and machine learning techniques, we find that BI funds are also tilted towards data-intensive projects. In Section 3.4, we find that compared to non-BI grants in neuroscience, BI grants are three times more likely to focus on AI and data-related areas. Lastly, the BI encourages collaborations between neurobiologists and scientists from statistics, physics, chemistry, mathematics, engineering, and computer and information sciences, facilitating knowledge spillover in neuroscience and outside the field. These distinct

[21] The program is set to run until 2026.

features set the program apart from previous neuroscience grants.

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 a 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[22]. Our final dataset encompasses 50,601 distinct startups, with the founded 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 takes the value of

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

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. Additionally, these startups hold an average of 2.85 patents, and 12% have founders with academic backgrounds.

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.[23] 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

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

process. AIPD uses machine learning to analyze all US patents from 1976 to 2020 and pre-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

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 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 of a startup's keywords as long as one of them contains *neuro* or *brain*. This results in a vector of 500 keywords .[24] 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.[25] In total, we find 220 Neuro-related CPC technology groups.

We identify 836 Neuro startups, with 87% in the healthcare sector and 8.01% in the IT sector. Our sample features well-known *Neuro startups* like Neuralink, Lumos Labs, and Neurotrack Technologies, which have gained significant media attention. As an alternative definition, we also consider relying directly on PitchBook's business descriptions or keywords provided by PitchBook. While the direction of findings is largely consistent using this definition instead of our patent-based definition, we prefer the patent portfolio approach for two reasons. First, business description keywords are subject to PitchBook's information, which relies on how the startup promotes itself. Our comparison of different versions of PitchBook reveals that a startup's description can vary from time to time. This could be problematic if startups self-select into describing 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. Moreover, PitchBook's descriptions are typically captured at a startup's inception, potentially missing significant shifts in its business focus. In contrast, patent portfolios offer dynamic insights into a startup's ongoing innovation activities.

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

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

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

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.

3.4. Research grants

We collect detailed information on BI grants from NIH and NSF websites, as detailed in Appendix A.2. Although the NIH has contributed more funding than the NSF, both have significantly supported the initiative. 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.

Although BI has made substantial investments in neuroscience research, its impact on scientific advancement and practical application remains unclear. To assess the impact of BI grants, we compare BI grants to non-BI neuroscience grants within the universe of NIH grants, focusing on citation counts of resulting publications and the nature of the research supported. We focus on the NIH grants because the NIH concentrates on medical research, allowing us to compare grants within the same research fields and mitigate the heterogeneity effects across different research fields. For instance, publications in medical research typically attract more citations than publications in other areas. Additionally, we identify non-BI neuroscience grants funded during the same period as BI, characterized by our *Neuro keywords*.

First, we proxy the scientific influence of research grants using the count of citations received by output publications that result from the grants. The citation count is a popular measurement as influential publications are cited more frequently by the following publications. BI-funded publications average 37.33 citations, while those from non-BI neuroscience grants average 31.79 citations. The 16% higher citation of BI publications is statistically significant at the 1% level, suggesting that research grants under BI have indeed made a positive contribution to advancing basic science, in accordance with the in Nature (2021) editorial article.

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 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

We collect the employee information of startups from the Dec 2022 version of LinkedIn. The LinkedIn dataset covers 80% and 86.48% of all startups and *Neuro startups* in our samples. This enables us to learn about the startup's employees and their CVs.

Our aim is to identify the employment history of startup's inventors, founders, and authors under publications of BI grants. Thus, we integrate LinkedIn, PatentsView, and Scopus data on an individual level. 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 initiate the process by comparing their names, followed by their 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 5. 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 owner of the patent and employer of the inventor. Similarly, for BI publication authors, we utilize their listed affiliations in the publications 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 experience of employee

To assess skilled labor, we pinpoint inventors and founders with prior academic experience, considering academia as the primary source of labor specialized in scientific research. In assessing academic experience, we consider three distinct types: 1) pursuing a doctoral degree, 2) holding a postdoctoral position, and 3) having work experience at universities and research institutes. For types 1 and 2, we exclude the areas of social science as unrelated to basic science. 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."

We consider two types of founders as academic founders: first, those who found a startup within five years after concluding their academic role or completing their doctoral degree, and second, those who hold concurrent academic employment when founding a startup. We set a five-year limit between the end of the academic position and the startup's founding year to ensure that these founders are transitioning to a new career path from academic careers and leveraging scientific knowledge gained during their academic tenure. The second type of founder is included because scientists may initiate a startup while continuing their academic research.[26]

We categorize academic inventors as inventors who begin working in startups following their academic roles or upon finishing their doctoral degrees. Unlike academic founders, where we apply a time restriction between academic roles and startups to capture a career transition, we impose no such limit for inventors. This is because choosing to become an inventor reflects a distinct career path, and previous academic job experiences indicate their capacity to integrate basic science into the innovation process. While we acknowledge that inventors can simultaneously engage in academic and startup ventures, we observe that most inventors tend to leave their academic positions before joining startups.

4. Empirical Analysis and Results

In a difference-in-differences (DiD) setting, our empirical analysis compares the treatment effects of an exogenous increase in the public funding of the treated with control groups. The exogenous shock we study is the BRAIN Initiative, a mission-oriented government program for mapping the human brain *Grand Challenge*. The outcome variables we study relate to private financing, labor, and innovation outcomes of the Neuro startups with non-Neuro startups.

4.1. Commercial Potential of BI

If BI was merely a scientific challenge without real commercial application then it may not be a relevant shock for our setting. To validate the relevance of BI, as a first step, we assess the commercial impact of the BRAIN initiative using three separate measures.

[26]For example, Robert Langer, the founder of Moderna, remained a professor at MIT

Our first two measures are provided by Masclans et al. (2024) and Marx and Fuegi (2020, 2022). Masclans et al. (2024) develop a large language model trained on a dataset containing renewed patents as positive examples. This trained model is then used to generate the ex-ante commercial potential of the publications. Using Masclans et al. (2024)'s commercial potential, we find that BI publications have a larger commercial potential than similar publications from the same period and past, thereby enhancing the commercially viable of the neuroscience area. Table A3 shows the average commercial potential of publications from BI grants is 0.78, compared to an average commercial potential of 0.49 for all publications [27]. To control for the heterogeneity among scientific areas– e.g., the availability of research grants– which may affect commercial potential, we compare 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 from NIH-funded non-BI grants in neuroscience (Non-BI grants). We first investigate whether BI grants have larger commercial potential than publications of Non-BI grants after 2014. Panel A of Table A3 shows 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 potentials of BI and non-BI grants is statistically significant at the 99% level, suggesting research under BI grants is more commercialization-focused than similar research grants in the sample period.

Given the special mission of BI grants, BI grants should have a positive spillover effect that enhances the overall commercial potential of the neuroscience field. In Panel A of Table A3, the average commercial potential of publications from NIH-funded neuroscience grants from 2007 to 2013 is only 0.64, notably lower than Non-BI grants after 2014. The difference in commercial potential between NIH-funded neuroscience grants from 2007 to 2013 and Non-BI grants after 2014 are statistically significant at the 99% level, suggesting BI grants have a positive spillover effect that enhances the commercial potential of entire neuroscience areas.

Marx and Fuegi (2020, 2022) measure the ex-post commercial potential of publications based on the patent citations of publications. A patent citing a publication indicates that the cited publication served as prior art for the patent, thus suggesting the ex-post commercial potential of the publication. 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. Recognizing that publications with high commercial potential may attract more patent citations, we conduct a Poisson regression analysis in Panel B of Table A3. Across all columns in Panel B, results consistently show that BI publications result in

[27] A DiD analysis is not feasible, as BI grants did not exist before 2014.

more patents than other or similar publications. More specifically, column 3, which includes controls for NIH-funded non-BI grants in neuroscience, commercial potential, scientific potential, and year-fixed effects, finds a coefficient of 1.485. This coefficient is statistically significant, indicating that BI publications receive approximately four times as many patent citations as other publications

Although our analysis demonstrates that BI grants enhance the commercial potential of the entire neuroscience field, it is equally important to determine whether startups effectively utilize the knowledge from BI grants. 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. Scientific research often serves as a foundation for innovations from various technological sectors. For example, AI began as a fundamental scientific discovery within computer science. Today, AI technology influences almost all industries. Therefore, we use LLM to identify the startup's neuroscience-related patents influenced by BI research output.

We train a model to identify unique features of patents resulting from BI publications, which are patents that directly cite BI publications. The LLM we use is SciBERT, a BERT model trained on 1.14M scientific articles. The SciBERT model is superior to the original BERT model, given its capacity to understand technology-related text. We further fine-tune the SciBERT model to solve the binary classification problem and calculate a score between 0 and 1 for how much BI influences a patent. To avoid this look-ahead bias, we develop a separate model for every year from 2016 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. Thus, For each focal year, t, the positive cases of the labeled data include only patents that cite BI publications and were filed from 2014 to year t-1. To construct the balanced labeled sample, we randomly selected two patent abstracts filed from 2003 to 2013 for each positive case (Masclans et al., 2024; Giczy et al., 2022).

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. The model of 2016 exhibits the poorest performance, with a weighted average F1-Score of 0.85. All other models achieve a weighted average F1-Score of over 0.9. In addition to conventional machine learning performance metrics, we also validate the performance of our model using patent citations. Patents that cite positive cases in label data—those that directly reference BI research—are highly likely to be influenced by BI research. Consequently, we tested whether our model could accurately predict patents that cite positive cases as patents influenced by BI research. Our model correctly predicted more than 75% of these patents as being influenced by BI research. Using our trained model, we find that 67% of neuroscience-related patents of startups are influenced by BI research.

4.2. 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 policy change. 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 validate this condition more formally in Table A5.

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 US$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, of which the BI was one of them. The top-down designation of BI, thus, presents an element of unpredictability and randomness, further supporting the shock's exogeneity. Yet, it is possible that in the months leading to the designation, some VCs have obtained information on the decision outcome. To address this, in our specification, we exclude deals occurring in the year of the event to ensure that the results are not driven by superior information that some VCs might have had. This choice is further motivated by the fact that the announcement occurred in April, almost in the middle of the year. Therefore, excluding financing events in 2013 ensures that the pre-and post-designations are correct; we exclude 2013 deals.

The selection of control variables 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 startups, providing a broad comparison across diverse sectors to distinguish the overarching patterns that differentiate Neuro startups. This broad control group is essential for establishing a baseline against which the specific impact of the BI on *Neuro startups* can be measured. Nevertheless, given that our definition of a Neuro startup is contingent upon the presence of patents with neuroscience keywords, and considering that only about 15% of startups hold patents while receiving VC investment, it is crucial to refine our control group to achieve 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 behavior indicates engagement in innovative activities, which are central to the value proposition of startups in the eyes of investors.

To further enhance the comparability, we refine our control group to include startups within the Healthcare sector that hold a patent as classified by PitchBook. The Healthcare sector 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*. Moreover, the time frame surrounding the BI provides a proximate economic context and, therefore, must be carefully selected. By choosing a window of three years before and after the policy implementation—excluding the actual year of the BI (2013)—we capture a temporal environment closely aligned with the period of interest. This approach delineates 2010, 2011, and 2012 as the pre-treatment years and 2014, 2015, and 2016 as the post-treatment years, denoted as [2010, 2016]. This time bracket ensures that we are considering the immediate impacts of the BI while allowing for a lag in the manifestation of these effects, which may not be instantaneous.

4.3. 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:

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

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. In our selection of industry classifications provided by PitchBook, which range from broad sectors to specific codes, we opt for the middle level of granularity: the Industry Group. 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. On the other hand, the broadest classification level, the Industry Sector, divides firms into only seven categories, including Healthcare.[28]

The first Y_{it} we study is the amount the VC invests at a financing round, i.e., round size. We first exclusively focus on the first financing round and then include all other rounds. This breakdown is essential for several reasons. First, the first financing round is often seen as a market signal of the quality and potential of a startup. It is typically based on the initial promise of the startup's technology and business model, before any major market validation. The risk profile of a startup changes as it progresses. Initially, the risk is highly skewed towards scientific and technological feasibility, which may be directly mitigated by public funding such as the BI. By examining the first rounds separately, we can isolate the effect of the BI on this early stage, which might be more influenced by the perceived scientific strength boosted by public funding. If public funding increases the perceived legitimacy or reduces the R&D risk of startups in the funded area, we would expect this to be most clearly

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

reflected in the first round of funding. Nonetheless, subsequent rounds are also important as they will tell us if this initial boost translates into an ability to attract further capital over time, which can signal sustained investor confidence and the potential for scale. By distinguishing between the first and later rounds, we can observe whether the influence of public funding like the BI extends beyond the initial endorsement of the startup's scientific foundation to its ongoing development and market validation.

In Table 2, we report the results of the OLS regression of Equation 1. The outcome variable, round size, is log transformed to account for the skewness of this variable. We include year, state, and industry group fixed effects. Panel A focuses exclusively on first-round financing, while Panel B includes all rounds. 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 panel A, 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 0.624 in the overall sample to 0.263 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 26.3% compared to other patenting startups in the healthcare—which offer the closest control group to *Neuro startups*— to 62.4%compared to all other startups, after the commencement of the BI. This result is statistically significant at the 1% to 5% levels.

In Panel B, we include all financing rounds. To control for the startup's lifecycle 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. Similar to the first round, the $Neuro \times Post$ coefficient remains positive and significant, though with smaller magnitudes than in the first rounds. The increases range from 16.8% to 39.3%, demonstrating a sustained effect across multiple financing rounds, which suggests the ongoing impact of the BI on investor behavior beyond the first round. Notably, the coefficient for the Neuro variable alone also shows significance, particularly in healthcare-focused rounds, suggesting that even outside the post-BI context, neuro startups tend to attract more financing compared to other sectors.

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 technological changes, *Neuro startups* have larger capital requirements to finance their operations. As such, we next turn to valuations, which also reflect the risk associated with neurotechnologies. In Table 3, we report the results from OLS regressions, paralleling the structure used for analyzing financing size, but this time focusing on the pre-money valuations of VC financing events. This figure shows the startup's valuation at the financing event net of the VC's investment amount. Again, we employ log transformation to mitigate the impact of skewness in the valuation data, including year, state, and industry group fixed effects to account for external influences that could affect valuation independently of the BI.

In both Panel A and Panel B of the valuation analysis, the $Neuro \times Post$ interaction term is significantly positive, indicating a robust post-BI increase in the valuations of *Neuro startups* across the first and subsequent financing rounds. Specifically, Panel A shows that first-round financing post-BI sees valuation increases between 27.4% in the healthcare sector and 37.3% 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*. Panel B extends this analysis to all financing rounds, incorporating controls for the progression in funding stages, where the valuation increases range from 16.0% to 32.2%. This consistent positive impact across multiple rounds demonstrates the BI's enduring effect on *Neuro startups* valuations, with a notable inherent valuation premium observed for *Neuro startups* in healthcare-focused rounds, emphasizing their increased attractiveness and reduced perceived risk to investors following the BI.

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 risk 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 de-risking the R&D process, offering more robust scientific foundations for *Neuro startups*, and increasing the attractiveness of these ventures to VCs. Furthermore, the persistent valuation premium across funding rounds may also indicate that the BI's impact is not limited to an initial surge in investor interest but extends to influence the sustained growth trajectory and perceived market potential of *Neuro startups*.

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".[29] We examine whether

[29]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.

the startup is generating revenue at the round. The results are reported in the Appendix Table A6. 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.

We also estimate the dynamic version of Equation 1, replacing $\text{Neuro}_i \times \text{Post}_t$ with year dummies. Figure 3 shows the coefficients where the control group is all other patenting startups. To have a balanced sample, we keep 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.

4.4. 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.

For every startup, we OLS estimate this variable 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 0.166 in the overall sample to a higher 0.214 in the healthcare sector, 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 16.6% to 21.4% 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*.

4.5. 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 the underlying characteristics of startups, particularly characteristics 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 embodied within the startup's patent portfolio.

4.5.1. Academic Startups

Our emphasis on human capital is inspired by the findings of Bernstein et al. (2017), which revealed that VCs consider information about a startup's human capital to be a significant indicator of the startup's quality at an early stage. If BI has reduced the technical risk of neuro startups, this could be reflected in the composition of the early employees of *Neuro startups*. Founder teams are likely to have a larger number of academic founders who possess more investable scientific knowledge or innovations emerging directly from their research labs, thereby enhancing the startups' attractiveness to VCs. As such, following the methodology in Section 3.5.1, we define an academic founder as a scientist who either found a startup within five years of departing academia or who simultaneously engages in academic work while establishing startups. We expect a greater presence of academics in the founding teams of *Neuro startups* relative to other startups following the initiation of the BI.

The univariate analysis shown in Figure 4 reinforces the notion that the BI has played a significant role in attracting academic founders to *Neuro startups*. Prior to the BI, *Neuro startups* already displayed a greater propensity to involve academics in their founding teams compared to non-neuro startups, as evidenced by a higher ratio of academic founders per startup. This gap widens post-BI, with the ratio for *Neuro startups* peaking at 0.65 in 2017, four years after the initiative's launch, before slightly retracting to 0.37 in the following years. This trend suggests a lagged effect of the BI, which is plausible given that the decision to establish a startup often follows a substantial gestation period during which academics may transition from research to entrepreneurship.

We also study this relationship more formally by estimating Equation 1, where the outcome variable, *Academic Founder*, is an indicator variable for whether the startup has at least one academic founder on its founding team. The results are reported in Table 5. Given the lag between the BI and the founding outcomes observed, here we run a dynamic specification, where the assignment of *Post* variable is based on *first VC year*=$t \geq T$ where T ranges from 2011 to 2019, in increments of one.[30] Similar to the trend in Figure 4, we do not see a statistically significant coefficient right after the shock. However, there is a discernible trend that post-BI, the likelihood of *Neuro startups* having academic founders increases, particularly from the year 2015 onwards. This trend peaks notably in 2017, with a coefficient of 0.136, which is significant at the 5% level, indicating a substantial increase in the propensity for *Neuro startups* to be founded by academics post-BI compared to the pre-BI period.

The trend's peaking in 2017 and its subsequent decline by 2019 (with coefficients dropping from 0.136 to 0.012) could be attributed to various factors, such as the absorption of academics with the intent of commercializing their knowledge by the markets, increasing competition in the market with *Neuro startups*, changes in BI funding allocations, or shifts in academic interest towards founding new ventures. This decline suggests that while the BI had a significant impact in the years following its launch, its influence on the composition of founding teams may wane over time or become integrated into the standard practice of venture creation in the neuro space.

[30] The inclusion of $T \leq 2011$ does not affect the results.

4.5.2. Innovation and Academic Inventors

The BI significantly enhances the attractiveness of *Neuro startups* to VCs by streamlining the innovation process in neuroscience. Research outputs funded by BI are notably more influential, as evidenced by the higher citation of BI-related publications compared to those from non-BI neuroscience grants, as detailed in Section 3.4. Furthermore, BI aims to facilitate the interaction between data science and neuroscience, prompting the adoption of AI in neuroscience. Given the BI's role in advancing neuroscience research, it is reasonable to anticipate an increase in innovation activities and AI adoption among *Neuro startups* post-BI, compared to other startups. We use multiple outcome variables to measure the innovation of startups, including startups' number of patents, breakthrough patents, AI patents, and the average adjusted citations per patent at year t. The breakthrough patents are patents that received more citations than the citations at the 90th percentile value within the same technology class and grant year. AI patents are predicted to contain AI components, as determined by Machine Learning in (Giczy et al., 2022). The adjusted cites are the number of cites over the average cites of patents in the same technology field and granted year.

BI also simplifies innovations by increasing the skilled labor supply. BI impacts directly, with 10% of NIH's BI grants dedicated to training promising postdoctoral researchers, and indirectly by infusing significant funds into the field, allowing researchers to train more PhD candidates. To quantify the skilled labor supply, we count the number of academic inventors newly hired by startups in a given year. The academic inventors are inventors with prior academic experience, as detailed in 3.5.

For all startups with at least one patent, we construct a panel of firm-year observations between the founding year of the startup to the year of VC exit, where we estimate:

$$Y_{it} = \beta_1 Neuro_i \times Post_t + \beta_2 X_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{2}$$

where for startup i in year t, Y_{it} includes the number of patents, breakthrough patents, the average adjusted citations of patents, and the number of academic inventors employed. Y_{it} following a Poisson distribution as a count variable with many zeros. 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. We also control for the log of the total amount of financing the startups have raised up to year t. This is to address that the larger funds *Neuro startups* raise post-BI may affect their innovation output.

Table 6 reports the results of this estimation. We find that *Neuro startups* produce more patents, breakthrough patents, and AI patents and hire more academic inventors compared to similar startups after the BI. Column 1 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 1 is 0.45 and statistically significant at 1%, suggesting that *Neuro startups* produce 1.57 ($e^{0.45}$) times more patents than other *non-Neuro startups* after BI. Although *Neuro startups* produce a larger number of patents, we are not sure about the quality of the patents. We further evaluate the quality of patents by counting the number of breakthrough patents that are the most valuable patents among patents for a given technology class and grant year. Column 5 investigates the role of BI on the breakthrough patents of *Neuro startups*. The coefficient of column 5 is 0.509 and statistically significant at 1% level, suggesting that *Neuro startups* produce 1.66 ($e^{0.509}$) times more breakthrough patents after the BI. Additionally, column 7 investigates whether the patent quality of *Neuro startups* is higher on average after the BI using the average adjusted citations per patent. The coefficient of column 7 is -0.209 and statistically insignificant, suggesting that not all patents of *Neuro startups* are of higher quality than other startups after BI. The possible explanation for the results in column 7 is *Neuro startups* could build a non-scientifically valuable but strategically valuable patent fence to protect their key breakthrough patents as there are a larger number of breakthrough patents for *Neuro startups* after BI. Moreover, we find *Neuro startups* produce more AI patents than other comparable startups. More specifically, the coefficient in column 9 is 0.734 and statistically significant at the 1% level, indicating that *Neuro startups* generate approximately 2.08 ($e^{0.734}$) times more AI patents as many AI patents as similar startups. We further find similar results in Columns 2, 6, 8, and 10 that estimate the coefficient using a sample period from 2010 to 2016. Therefore, *Neuro startups* not only produce more patents and breakthrough patents but also increasingly utilize AI technology post-BI. Additionally, *Neuro startups* establish patent fences to protect their key breakthrough patents. To further refine our analysis, the untabulated table finds that neuroscience-related patents receive a larger adjusted citation and are more likely to be breakthrough patents after BI, suggesting that the neuroscience space benefits from BI and produces better technology.

Post-BI, *Neuro startups* might experience an increase in the availability of academic inventors due to BI's direct and indirect influences on university funding and the expansion of the academic researcher pool. *Neuro startups* may find it easier to find academic inventors after BI as the BI, directly and indirectly, provides more university funding and results in more academic inventors. We measure the supply of skilled labor using the number of newly hired academic inventors. Columns 3 and 4 of Table 6 report the results of Poisson regression of the number of newly hired academic inventors on the interaction of *Neuro* and Post. The coefficient in column 3 is 0.726, significant at the 1% level, indicating that post-BI, *Neuro startups* hire over two times more academic inventors than other startups. This trend remains consistent when examining data from 2010 to 2016 in column 4. Babina et al. (2023) find that when a researcher's federal budgets are cut, her chances of stepping into an entrepreneurial setting decline. They, however, do not differentiate between the founders and scientists who work for the startup. We analyze academic founders in Table 5 and academic inventors in Table 6 separately and find similar results.

4.5.3. 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 A7, 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 A8 and A9, we repeat the exercise in Table 2 and 3, 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)[31] 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.

4.6. 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:

$$Y_{it} = \beta_1 \text{BI Employer}_i \times \text{Post}_t + \beta_2 X \mathit{BI\ Employer} + \beta_3 X_{it} + \text{Fixed effects} + \upsilon_{ijt}, \quad (3)$$

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 × *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 7. In Columns (1-3), we include industry, year, state, and round fixed effects, and we add firm fixed effects, in Columns

[31]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.

(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 2010 and 2016 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 × *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 2010 and 2016. 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. Conclusion

We study how strategic public investments can mitigate technical risks and make nascent technologies more attractive to private investors. In a different-in-difference setting, we examine the Brain Research Through Advancing Innovative Neurotechnologies (BRAIN) Initiative, a government program with the goal of producing a map of the human brain. Our findings reveal that post-BI, neuro startups not only received larger VC investments at higher valuations but also exhibited enhanced innovation outputs, higher integration of AI technologies, and more successful exits. This suggests that government programs like the BI play a crucial role in bridging the funding gap for high-risk, high-reward scientific endeavors by reducing technical risks and fostering interdisciplinary collaboration.

Moreover, the presence of skilled labor, particularly STEM academics transitioning into entrepreneurial roles, highlights the importance of human capital in driving the success of these ventures. The increased patenting activity and the broader scope of technological areas post-BRAIN Initiative indicate a thriving innovation ecosystem that benefits from public funding. The positive externalities of such programs extend beyond the immediate scope of neuroscience, fostering advancements in related fields and attracting diverse sectoral investments.

Our study also addresses potential concerns regarding the endogenous attraction of investors to promising neurotechnologies independent of government intervention. The lack of pre-trend VC activity in the neuro space and the deliberate selection of the BRAIN Initiative among other scientific projects support the exogeneity of the public funding shock. Additionally, our focus on the human capital trained through BRAIN Initiative grants provides direct evidence of the initiative's treatment effects, further validating our findings.

In summary, mission-oriented public funding can significantly influence the trajectory of scientific and technological innovations by making them more viable for private investment. The BRAIN Initiative exemplifies how targeted government support can catalyze breakthroughs, enhance interdisciplinary research, and ultimately contribute to the commercialization of groundbreaking technologies.

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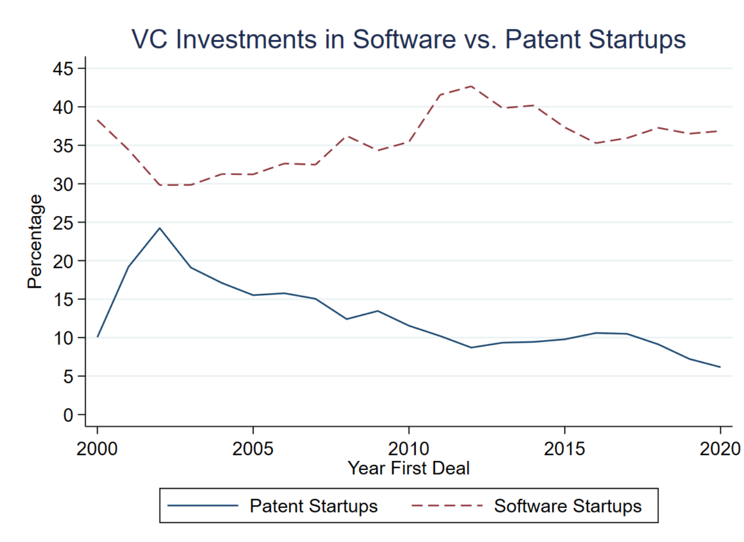
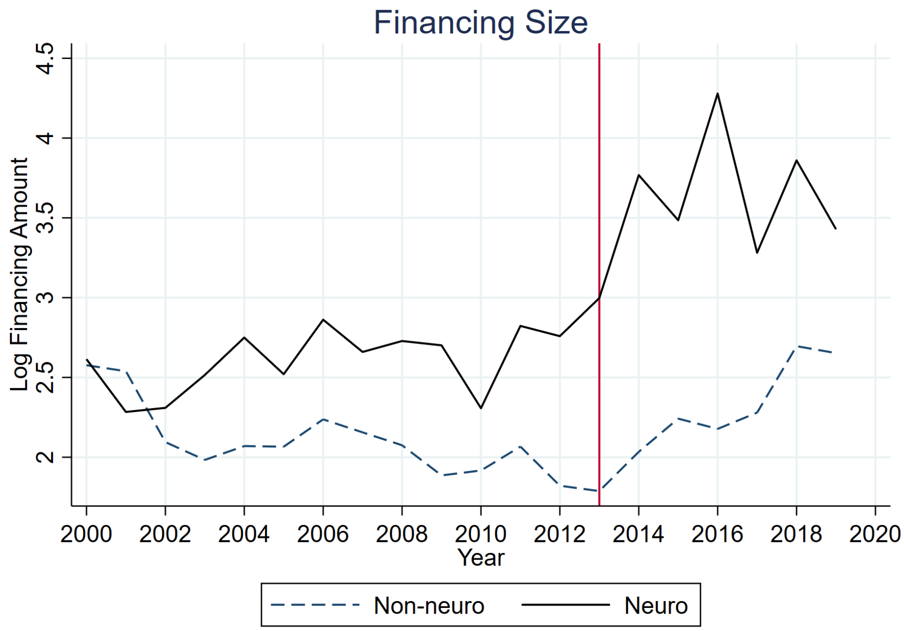


Figure 1. **VC Investments in Software vs. Patent-holding Startups**

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.



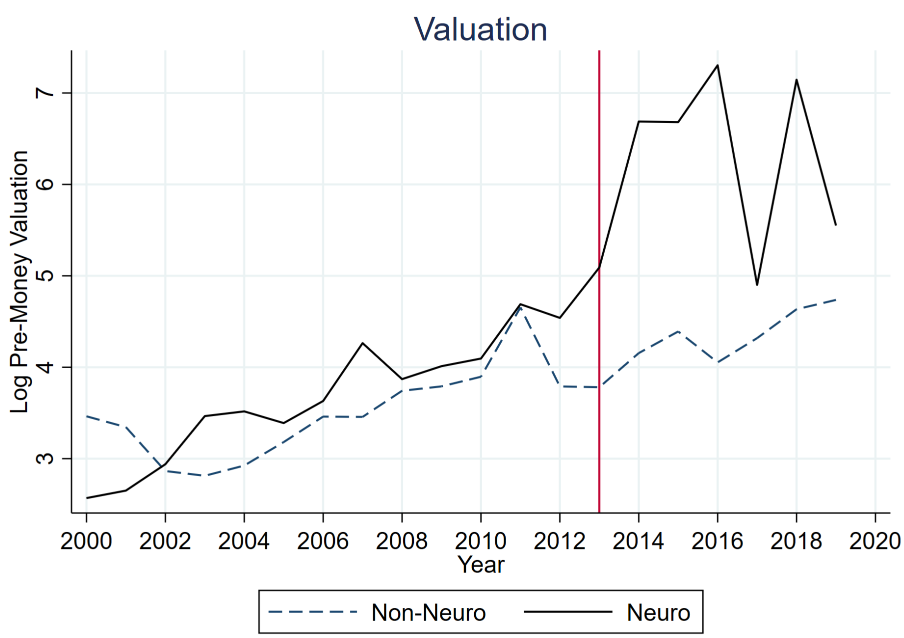


Figure 2. **Financing and Valuation of Neuro-Startups**

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.

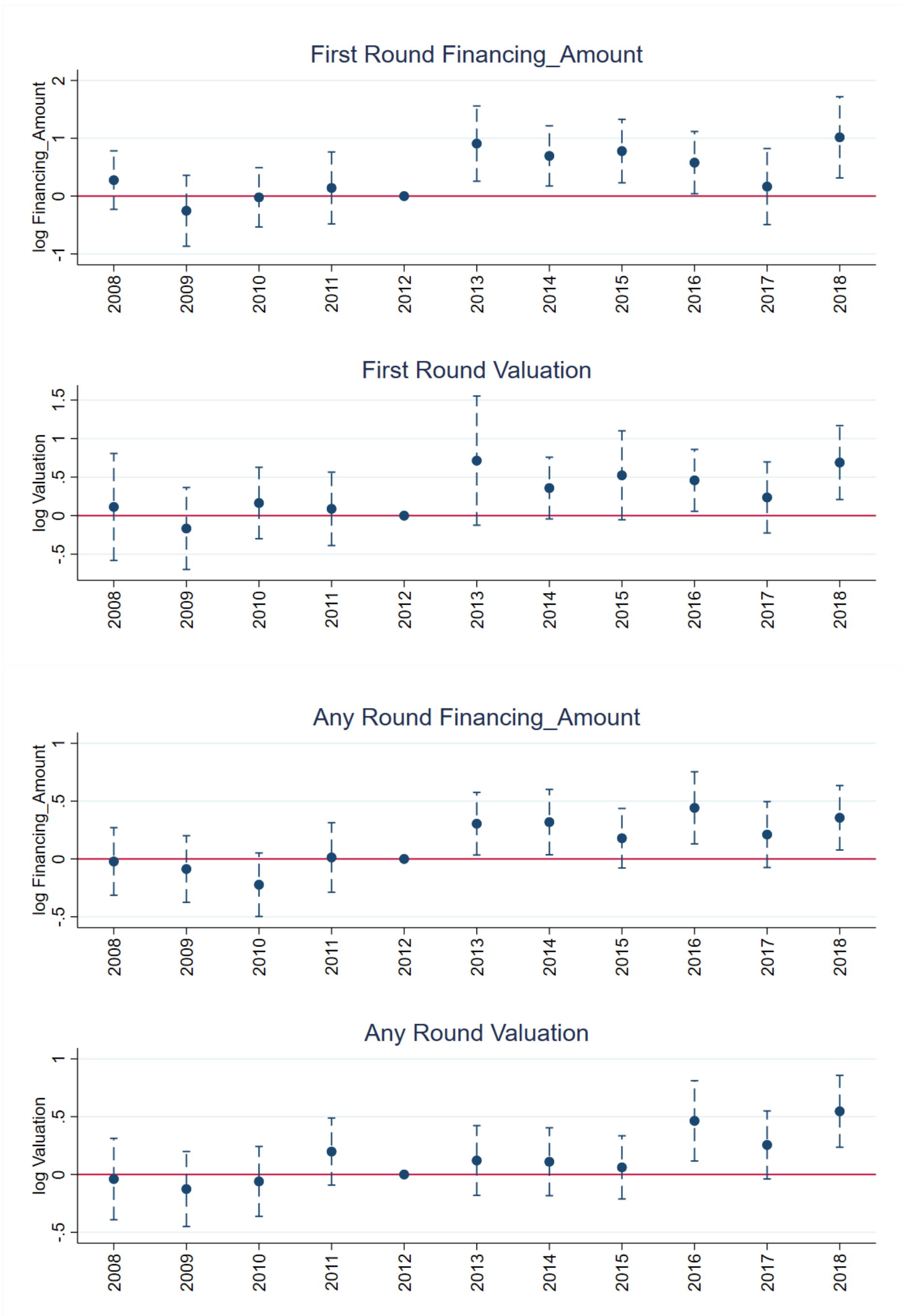


Figure 3. **Difference-in-difference estimates for financing and valuation: Neuro vs Other Healthcare**

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 top two figures only include first rounds and the bottom 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.

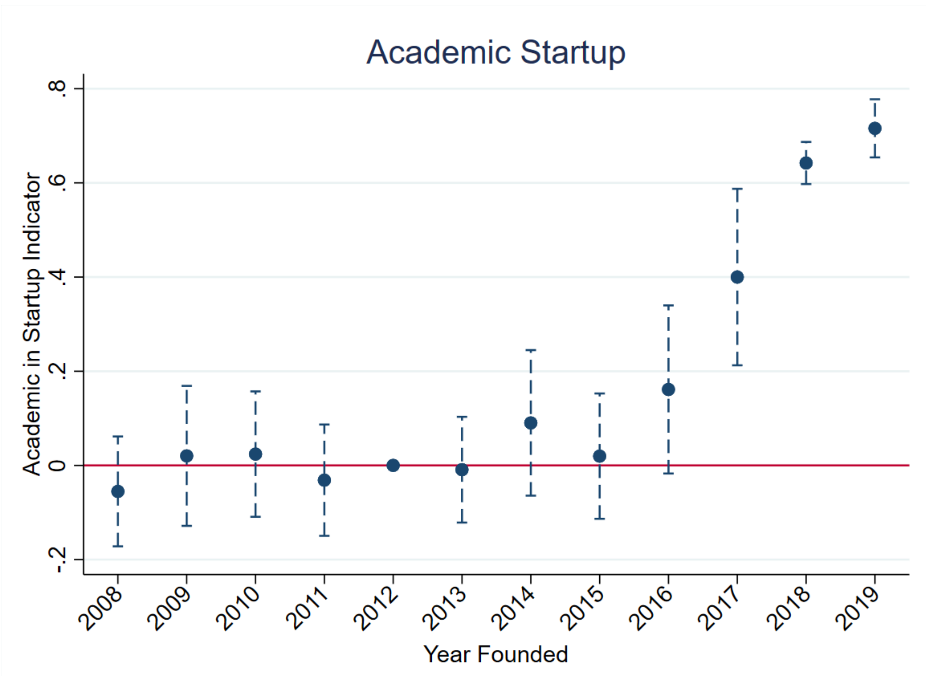


Figure 4. **Difference-in-difference estimates for Academic Startups: Neuro vs Other Healthcare**

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.

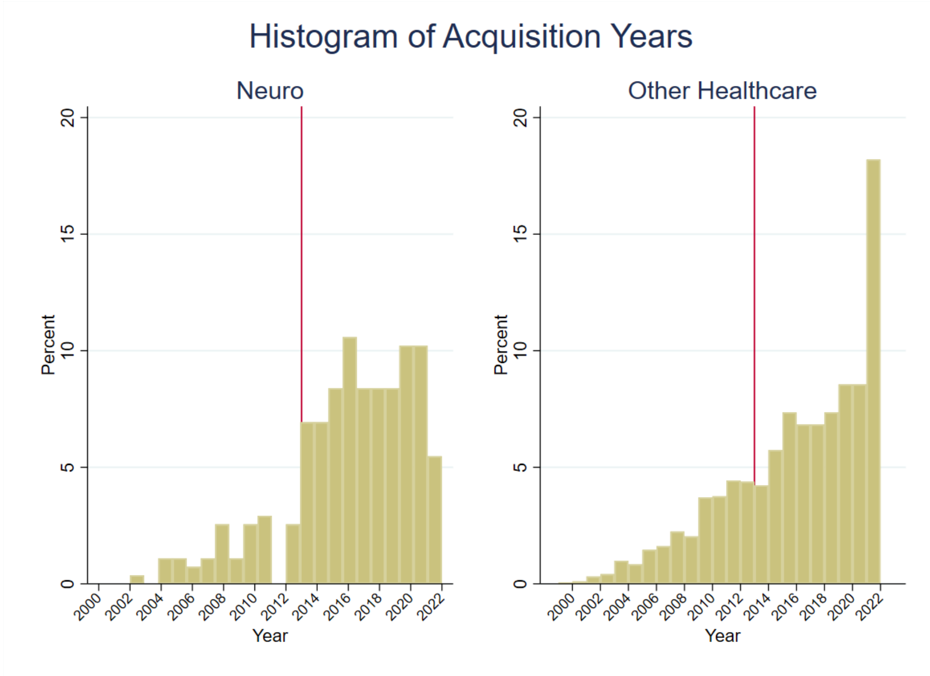


Figure 5. **Acquisitions of Neuro and other healthcare startups**

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

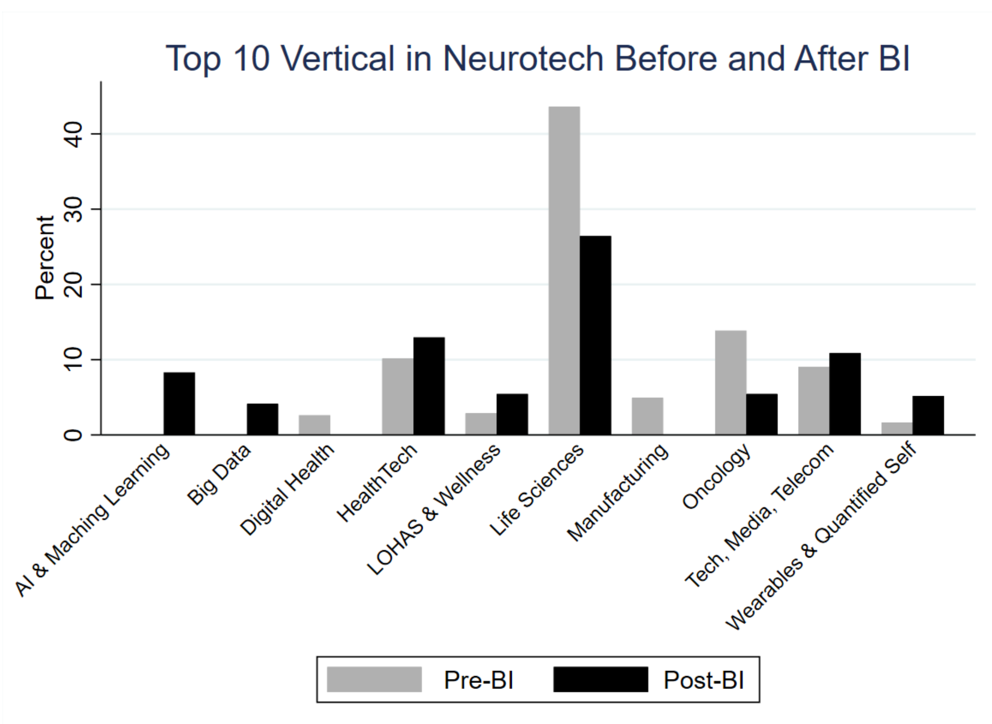


Figure 6. **Industry Verticals of Neuro Startups before and after the BI**

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: Startups 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 reports results from OLS regressions estimating Equation 1, where the dependent variable is the log of VC investment amount. 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	**Ln(round size $)**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.624	0.392	0.307	0.263
	(5.973)***	(3.633)***	(1.944)*	(2.068)**
Neuro	0.037	-0.029	0.079	0.037
	(0.526)	(-0.395)	(0.627)	(0.465)
Ln(# VCs)	0.739	0.720	0.575	0.864
	(67.197)***	(30.752)***	(15.959)***	(20.351)***
Observations	39,142	8,675	3,687	3,226
Adj R-squared	0.195	0.185	0.156	0.211
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	0.393	0.232	0.210	0.168
	(5.206)***	(3.058)***	(2.098)**	(2.490)**
Neuro	0.110	0.109	0.134	0.184
	(2.052)**	(2.009)**	(1.706)*	(4.135)***
Ln(# VCs)	0.848	0.861	0.845	1.022
	(107.326)***	(62.886)***	(42.895)***	(52.796)***
Observations	87,499	26,903	11,916	9,918
Adj R-squared	0.337	0.344	0.350	0.282
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 3: Valuation. This table reports results from OLS regressions estimating Equation 1, where the dependent variable is the log of VC Pre-Money Valuation. 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	**Ln(Pre-Money Valuation $)**			
	All	Patenting Startups		
		Any	[2010-2016]	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.373	0.222	0.352	0.274
	(3.650)***	(2.070)**	(2.201)**	(2.189)**
Neuro	-0.010	0.020	-0.009	0.003
	(-0.153)	(0.291)	(-0.081)	(0.042)
Ln(# VCs)	0.297	0.261	0.237	0.297
	(26.768)***	(11.499)***	(7.052)***	(7.795)***
Observations	18,344	4,976	2,176	1,834
Adj R-squared	0.088	0.080	0.076	0.093
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	0.322	0.170	0.160	0.271
	(3.598)***	(1.872)*	(1.441)	(3.355)***
Neuro	0.154	0.207	0.287	0.222
	(2.576)**	(3.377)***	(3.507)***	(4.104)***
Ln(# VCs)	0.394	0.401	0.397	0.488
	(42.196)***	(24.679)***	(17.545)***	(21.039)***
Observations	47,619	17,078	7,794	6,048
Adj R-squared	0.443	0.462	0.464	0.157
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 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. *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			
	All	Patenting		
			[2010,2016]	
				Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.166	0.078	0.142	0.214
	(4.187)***	(1.752)*	(1.999)**	(2.646)***
Neuro	0.077	0.033	-0.050	-0.100
	(2.916)***	(1.148)	(-0.839)	(-1.547)
Ln(Raised before exit)	0.096	0.123	0.124	0.132
	(57.422)***	(29.554)***	(19.692)***	(11.731)***
Observations	11,074	2,498	925	430
R-squared	0.344	0.362	0.416	0.417
Industry FE	Y	Y	Y	Y
First VC Year FE	Y	Y	Y	Y
Exit Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Table 5: 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. *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.

Academdic Startup Indicator				
	All	[08-18]	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 reports regression results of a Poisson estimation of Equation 2 for a firm-year panel, where the dependent variables in columns 1 and 2 are the total number of patents filed (and eventually granted) in year t. The dependent variables in columns 3 and 4 are the number of academics hired in the year. In columns 5 and 6, the dependent variables are 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. The dependent variables in columns 7 and 8 are 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. In columns 9 and 10, the dependent variables are the number of patents that contain AI technology (Giczy et al., 2022) filed (and eventually granted) in year t. A unit of observation is firm-year, from the founding year to the year of VC exit. The panel only includes patenting firms. *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). *total raised* is the total amount of financing the company has raised up to that year. The t-statistics (in parentheses) are clustered at the startup level, with ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

#Patents		# Academic Inventors Hired		#Breadth Patents		Avg. Adjusted Cites		#AI Patents	
All Years	[2010, 2016]	All Years	[2010, 2016]	All Years	[2010, 2016]	All Years	[2010, 2016]	All Years	[2010, 2016]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
0.450	0.469	0.726	0.636	0.509	0.601	-0.209	-0.148	0.734	0.764
(3.130)***	(3.922)***	(2.680)***	(2.537)**	(2.956)***	(3.437)***	(-1.288)	(-1.365)	(2.942)***	(2.964)***
0.062	0.052	0.030	0.051	0.043	0.048	-0.047	-0.038	0.076	0.088
(4.688)***	(2.647)***	(1.003)	(1.012)	(2.722)***	(2.035)**	(-4.435)***	(-1.845)*	(3.624)***	(3.327)***
91,210	26,307	38,387	9,655	45,520	11,086	80,385	22,751	36,616	10,340
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 7: 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	
			[2010-2016]			[2010-2016]
	(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(# VCs)	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	
			[2010-2016]			[2010-2016]
	(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

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.1 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 Figures and Tables

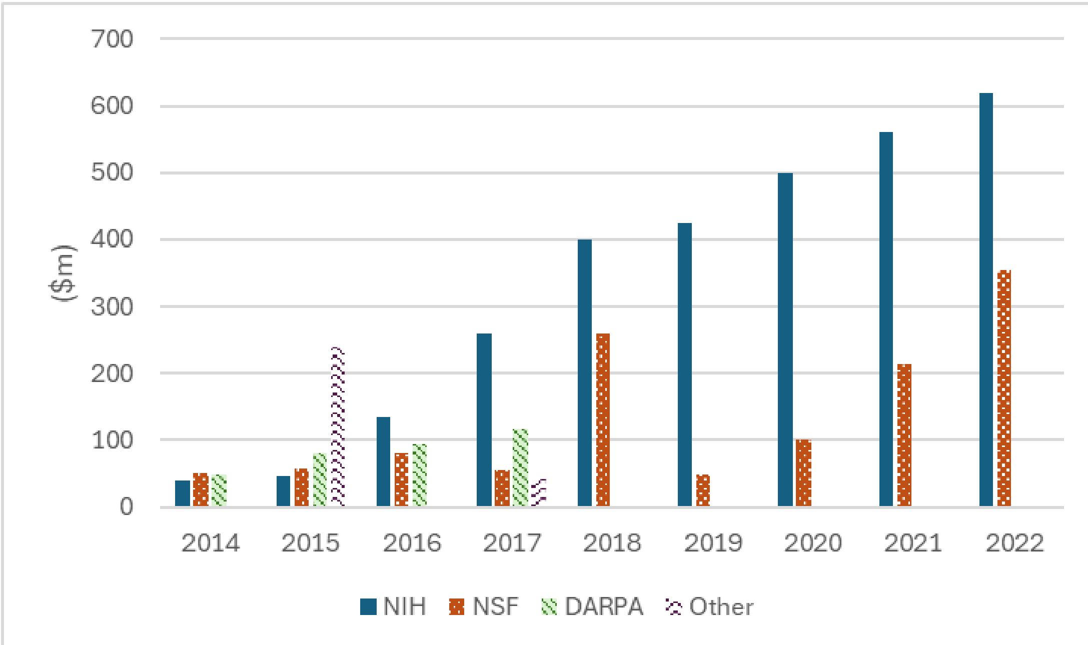


Figure A.1. **Total BRAIN Initiative Funding per Agency**

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.

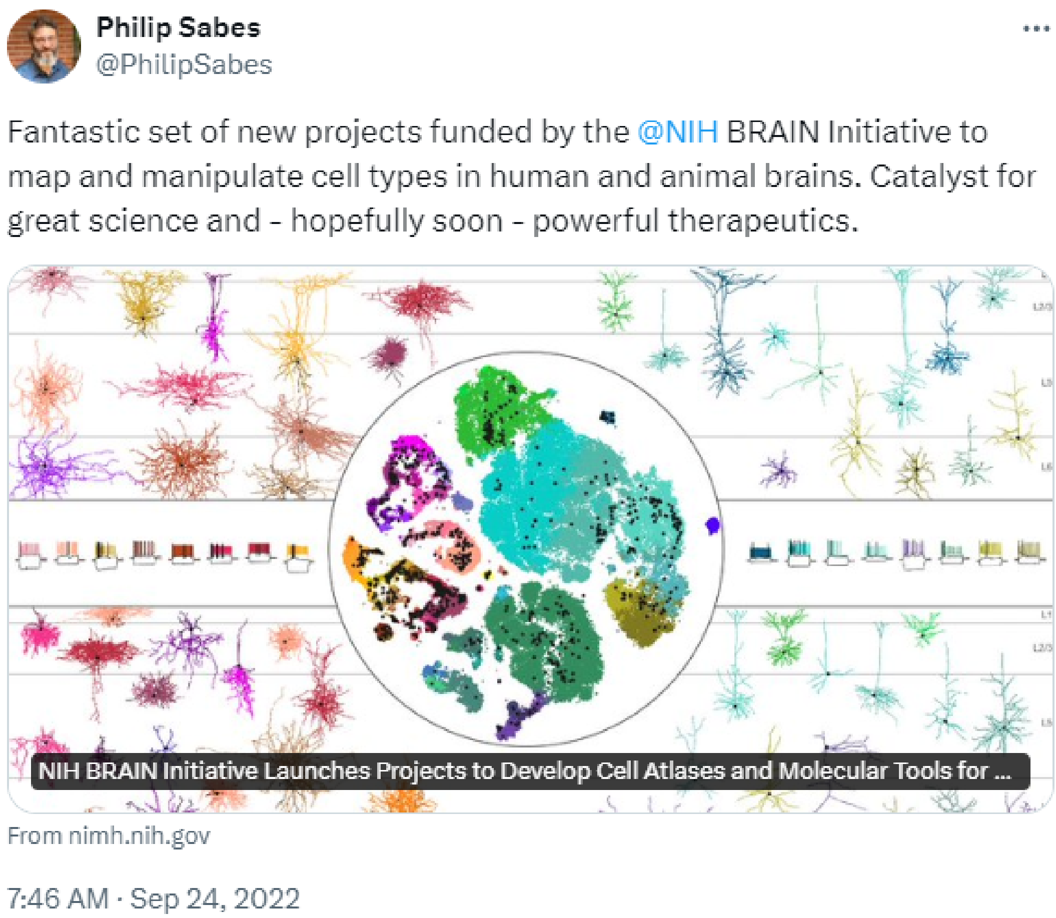


Figure A.2. **An Example of an Academic Co-founder**

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, 3,4,5, 6,A6, A8,A9
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, 3,4,5, 6,A6, A8,A9
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 7
Ln (# VCs)	The natural logarithm of the number of VCs in the round. Sources: PitchBook	Table 2,3, 7,A6,A8,A9
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$)	The natural logarithm of VC financing amount. Sources: PitchBook	Table 2,7, A8
Ln(Pre-Money Valuation$)	The natural logarithm of VC Pre-Money Valuation. Sources: PitchBook	Table 3, 7,A9
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 A6

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 Viability of BI research This table compares the commercial potential of BI research against similar research. Panel A utilizes the ex-ante commercial potential of publications from Masclans et al. (2024). It divides the publications into three groups: Group A includes publications from BI grants; Group B encompasses all publications from NIH-funded non-BI grants in the neuroscience areas after 2014; and Group C comprises publications from NIH-funded non-BI grants in the neuroscience areas from 2007 to 2013. Panel B presents the results of Poisson regressions on the #citations received by publications on the BI grant indicator. The key dependent variable, #citations, is 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 the NIH indicator, one for publications from NIH-funded non-BI grants in neuroscience areas, and measures of commercial and scientific potential. All regressions include year-fixed effects. Columns 1 and 3 report regression results for the full sample, whereas Column 2 specifically examines publications from NIH-funded grants.

Panel A: Commercial Potential			
	BI Grant (A)	Non-BI post 2014 (B)	(A-B)
Commercial Potential	0.78	0.69	0.09***
	Non-BI post 2014 (B)	Non-BI from 2007 to 2013 (C)	(B-C)
Commercial Potential	0.69	0.64	0.05***
Panel B: Patent citations of publications			
	(1) #Citations	(2) #Citations	(3) #Citations
BI Grant	2.022	1.192	1.485
	(0.301)***	(0.307)***	(0.301)***
NIH			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

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	1.00	0.94	0.97	17
1	0.86	1.00	0.92	6
Maro avg	0.93	0.97	0.95	23
Weighted avg	0.96	0.96	0.96	23

2018

	Precision	Recall	F1-Score	Support
0	0.97	0.99	0.98	85
1	0.98	0.93	0.96	46
Maro avg	0.97	0.96	0.97	131
Weighted avg	0.97	0.97	0.97	131

2016

	Precision	Recall	F1-Score	Support
0	0.86	0.89	0.88	28
1	0.82	0.78	0.80	18
Maro avg	0.84	0.84	0.84	46
Weighted avg	0.85	0.85	0.85	46

2019

	Precision	Recall	F1-Score	Support
0	0.93	0.95	0.94	114
1	0.86	1.00	0.92	63
Maro avg	0.92	0.91	0.91	177
Weighted avg	0.92	0.92	0.92	177

2017

	Precision	Recall	F1-Score	Support
0	0.96	0.98	0.97	55
1	0.97	0.93	0.95	30
Maro avg	0.96	0.96	0.96	85
Weighted avg	0.96	0.96	0.96	85

2020

	Precision	Recall	F1-Score	Support
0	0.96	0.96	0.96	133
1	0.94	0.93	0.93	81
Maro avg	0.95	0.94	0.95	214
Weighted avg	0.95	0.95	0.95	214

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: 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 A7: 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 A8: 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 A9: Valuations without AI and Big Data Startups. This table repeats the exercise in Table 3, 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