Venture Capital Response to Government-Funded Basic Science*

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Abstract

Science-based R&D can deter venture capitalists due to high technical uncertainty. We study whether mission-oriented public funding—supplying basic science as a public good—fosters VC investment. Our quasi-natural experiment is the BRAIN Initiative (BI), a large-scale government program aimed at mapping the human brain. Using machine learning, we first find large spillover effects of BI in neurotech. Our difference-in-differences analysis shows that BI raised the probability of receiving VC, led to larger funding rounds at higher valuations, and resulted in more successful VC exits for neurotech startups. The mechanisms suggest a reduction in technical uncertainty: (1) an expanded supply of skilled academic labor, (2) increased innovation activity and (3) deeper integration with complementary technologies like AI and big data. Our findings suggest that government-backed science can catalyze private investments in emerging fields.

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1. Introduction

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

Venture capital (VC) investments seem to reflect these ideas. Although VC is a major market mechanism in financing innovation (Kortum and Lerner, 2000), there are concerns about the increasing focus of VC funds on the IT sector to the detriment of nascent technologies built on new science. These technologies are crucial for addressing significant societal challenges, such as climate change and Alzheimer's disease. Consequently, underinvestment in them leads to substantial welfare loss.[3] Lerner and Nanda (2020) argue that the typical VC model—characterized by small funds with a finite life of 10-12 years—has limitations in addressing the technical uncertainty in new science. Commercializing emerging science requires longer timelines and often high upfront R&D costs, not amenable to how VCs address the Knightian uncertainty—i.e., unknown variance—of the entrepreneurial process.[4] Kerr, Nanda, and Rhodes-Kropf (2014) argue that VCs finance startups in stages, with each stage serving as an experiment that reveals information about the project's viability and reduces uncertainty. The IT sector aligns with the VC criteria because technological advances such as cloud computing have lowered the cost of early-stage experimentation in software (Ewens, Nanda, and Rhodes-Kropf, 2018). In contrast, reducing uncertainty in new sciences requires large-scale investment beyond the scale of most VC funds. Such uncertainty also deters potential entrepreneurs—typically academic scientists with secure, salaried positions—from entering entrepreneurship due to the high opportunity costs (Hall and Woodward, 2010).

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

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

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

[4] Knight (1921) argues that entrepreneurs face uncertainty, fundamentally different from risk. Under risk, success probabilities and expected values are known. These are unknown under uncertainty.

Kerr et al. (2014) thus suggest that institutions such as government and academia are essential in enabling experimentation in new science.

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

Nonetheless, the effect of public funding of science on VC investments is far from clear. Public funds may be allocated to projects far from commercial viability (e.g., cosmology or fusion energy). Public funds could even crowd out VCs by (i) subsidizing entrepreneurial R&D and lowering the demand for dilutive VC capital, or (ii) competing with VC-backed startups over top talent and research infrastructure (Goolsbee, 1998). On the other hand, R&D subsidies to startups may enable prototyping or certification and thus crowd in VCs (Lerner, 1999; Howell, 2017). Public funding mechanisms vary significantly, and their efficacy depends crucially on their design (Howell, 2024). In this paper, we study whether large-scale, mission-oriented public funding of science fosters VC investments.

We use the BRAIN Initiative as a laboratory to study this question. Brain Research Through Advancing Innovative Neurotechnologies (BRAIN) is a government "big science" or "moonshot",[7] program in neuroscience. Anecdotal evidence suggests the coordinated nature of these programs is effective in resolving scientific bottlenecks (Mazzucato, 2021).[8] One

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

[6] Perine (2000)

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

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

example is the Human Genome Project (HGP), which aimed to sequence DNA bases in the human genome and spurred the emergence of the market for genetic therapy. Similar to the HGP, the BRAIN Initiative (hereafter BI) has a mission: mapping the human brain. Leading neuroscientists proposed this mission through two influential papers.[9] They argued that overcoming the longstanding stagnation of neuroscience at the single-neuron level required a large-scale, coordinated effort to understand macro-level brain activity. President Obama designated this agenda as a Grand Challenge in 2013. This foundational knowledge has clear implications for neurological disorder treatment (e.g., Alzheimer's, Parkinson's). To achieve this mission, BI has made significant investments in developing tools and methods that can directly contribute to wider technological areas–e.g., brain-computer interfaces, and artificial intelligence (The White House, 2013; NIH, 2014a). The US government has spent over $4.8B in funding the BI until 2022, and the program is set to run until 2026.

BI's introduction allows us to study cross-sectional variation in VC investments in a difference-in-differences (DiD) design. We test whether the expectation of scientific advances, as a result of the government's investment, reallocates VC investment into the treated group: neurotech ventures. We construct a comprehensive dataset with information on startup financing, innovation, and employees. We compile a sample of US startups receiving their first VC funding round between 2000-2019 using Pitchbook and follow their outcomes until 2022. We link this to Revelio Labs (LinkedIn) data for information on startup employees and their career history. We specifically identify the academics who have founded or worked for these startups. We also add information on the startup's patenting activity from USPTO and define a startup as a *Neuro startup* if it has at least one patent related to neuroscience based on the textual analysis of the patent's technology classes. Our results are robust when using non-patent-based classifications, too. To examine the direct impact of the BI, we collect data on grants, including the dollar amount, organizations involved and output publications, from the websites of funding agencies. We link publications to Scopus for information on citations and co-authors.

We first explore if VCs are more likely to invest in a *Neuro startup* post-BI. Receiving VC is a major milestone in the life cycle of high-growth startups. Gompers, Gornall, Kaplan, and Strebulaev (2020) document that VCs reject 100 other startups for every one they ultimately fund. If the BI reduces the uncertainty around *Neuro startups*, we should expect more of them to receive VC. While Pitchbook provides data on startups that successfully raise capital, we also require a credible set of comparable firms that may have sought external funding–even if they did not ultimately secure it. For this, we draw on the Ewens and Marx

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

(2023) dataset covering the founding years of all patenting firms in the economy. we compare the probability of securing VC funding for *Neuro startups* against other patenting firms in the same technology subclasses. Our first key finding is that, following the BI, *Neuro startups* are significantly more likely to receive venture financing.

We then turn to the intensive margin, comparing VC-backed *Neuro startups* with other VC-backed startups and narrower control groups within this set. This includes startups in the healthcare sector, startups focused on curing cancer–before the US government announced the Cancer Moonshot program–[10] and those patenting in similar technologies. The literature argues that VCs stage capital infusion to keep an abandonment option; through smaller, conditional investments, VCs collect information about a project's prospects (Gompers, 1995; Cornelli and Yosha, 2003; Bergemann and Hege, 2005; Ewens et al., 2018). Thus, if VCs anticipate reduced technical uncertainty due to the BI, they are expected to increase their investment size. This reduction in uncertainty should also lower the discount rate used in calculating the project's net present value, consequently increasing its valuation.

Consistent with these hypotheses, we find that *Neuro startups* receive between 21% and 50% larger investments from the VCs post-BI depending on the control groups. Such investments are also made at valuations that are 23% to 41% higher. We also provide direct evidence that within *Neuro startups* those with more proximity to the BI receive more favorable funding. We measure proximity to the BI along three dimensions: (i) labor exposure captured by hiring BI-funded researchers; (ii) IP exposure reflected in patents leveraging BI-generated knowledge; and (iii) geographic proximity, based on the startup's location relative to BI-funded institutions. Across these measures, greater BI exposure is associated with increased VC investments and valuations.

We next examine the outcomes of these investments and find that VCs are likelier to successfully exit their neuro investments–via either IPOs or acquisitions.[11] These exit patterns indicate that not only VCs but also the broader market perceives an enhanced upside for neuro startups. Moreover, VCs tend to exit neurotech investments more quickly, implying a higher internal rate of return. The shorter holding period also suggests that post-BI, R&D timelines in neurotech become better aligned with VCs' limited fund life. Our back-of-the-envelope calculations estimate that each dollar of BI funding was matched with $1.1 of VC investments[12] and led to an additional $2.5 in exit value.

We propose three non-mutually exclusive channels to explain the more favorable VC

[10] Another mission-oriented program announced in 2016.

[11] Following Ewens and Rhodes-Kropf (2015), a successful acquisition is defined as an exit value exceeding twice the capital invested.

[12] The additional private investment caused by the BI is likely to be larger when one accounts for other investors (e.g., public firms, PE-backed firms, angel-backed, etc.)

financing and outcomes: 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. We observe a higher likelihood of inventors in *Neuro startups* coming from academic backgrounds after the BI.

Neuro startups also 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 leverage 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. This indicates more integration of data science into neuroscience-related technologies.

BI played a role in this shift in neuroscience. The human brain comprises 86 billion neurons, forming over 100 trillion connections (Nature, 2021). To Decode this complex network, BI funded the construction of extremely large public datasets[13] and computational infrastructure for analyzing these gigantic datasets (Zador, Escola, Richards, et al., 2023). We find that NIH's BI grants are three times more likely to fund data science-related areas than conventional NIH neuroscience grants. Furthermore, the human brain is an extremely energy-efficient and powerful computer. Understanding the computation and communication mechanisms of the brain, at the core of BI, is synergistic with fields like AI, robotics and brain-computer interfaces. Consistently, we find that *Neuro startups* founded post-BI are more likely to incorporate these technologies. This raises a reverse causality concern–where VCs invest in *Neuro startups* because of AI applications rather than the BI. While our sample ends before the current AI boom, we show our results persist even after excluding ventures that leverage AI or big data.

[13] 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."*

We also examine the validity of the DiD's parallel trends assumption. This assumption would be violated if, for example, the inherent promise of neuroscience would have attracted VC investment independent of the BI. Several observations mitigate this concern. First, our dynamic estimations show no evidence of a pre-trend in the neurotech prior to 2013. Second, the scale of the BI, with over \$4.8 billion in government funding, dwarfs the typical investment capacity of individual VC funds, which average \$145 million per fund.[14] Third, unlike VCs that fund businesses, BI funded university research. These two financing mechanisms target different stages of technology development and are not substitutes. The coordinated nature of the BI is also distinct. It is unlikely that the VCs would *coordinate* to fund a non-excludable public good like a comprehensive brain map.

Still, unobservable advances in neuroscience could have coincided with the BI, or even spurred the government to join an already booming market. Anecdotal evidence suggest otherwise; leading up to the BI, even pharmaceutical companies, traditionally major investors in neuroscience R&D, were cutting their expenditures in the field due to high uncertainty and failure rates.[15] We investigate this more formally by leveraging richer information on listed firms' innovation. We use patent valuation data developed by Kogan, Papanikolaou, Seru, and Stoffman (2017) and find an increase in public markets' valuation of neurotech only after the BI's announcement. This suggest that the program timing was unrelated to pre-existing advances.

Both VCs and public markets quickly reacted to the BI's announcement, anticipating its impact. Ex post, real outcomes–i.e., BI's scientific output–met these anticipations. We use three distinct measures to assess whether BI-funded science was technologically influential. The first two, developed by Marx and Fuegi (2020, 2022) and Masclans, Hasan, and Cohen (2024), rely on the idea that publications cited by patents are more commercializable. Along both measures, BI-funded research appears more commercializable than comparable neuroscience publications. However, citations likely underestimate the BI's influence due to the imperfect appropriability of basic science innovation. Patents tend to cite prior art immediately related to the invention, which implies that the broader scientific foundation, or the tools and methods adopted in the invention process, are less frequently cited.[16] Another issue arises from the truncation issue in patent citations. This is specifically relevant because the BI occurs in the second half of our sample. A growing literature, including

[14] This is based on all Pitchbook's US VC funds.

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

[16] 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.

USPTO's economists, suggest that machine learning models can overcome some of these limitations (Toole, Pairolero, Forman, and Giczy, 2020; Lerner and Seru, 2021; Masclans et al., 2024). Inspired by their methodologies, we employ a large language model (LLM) to identify patents influenced by BI-funded research and tools. We fine-tune a SciBERT model[17] using a labeled dataset that includes positive cases—the titles and abstracts of research papers resulting from BI research outputs—and negative cases, consisting of neuroscience publications before the BI. The model estimates that the BI has influenced at least 66% of all *Neuro startups'* patents.

Our work informs the current debates on the efficiency of public R&D funding through institutions like NIH or NSF. US VCs have funded novel technologies and are a role model for the rest of the world. However, our results indicate that they do not operate in a vacuum and US national science institutions have been instrumental in their success. This relates us to a large body of literature that studies the interactions between public R&D expenditure and private investments. Fleming, Greene, Li, Marx, and Yao (2019) show US corporations and startups increasingly rely on government-backed innovation. Myers and Lanahan (2022) document that public funds initiate significant spillovers, even in distant technological areas.

Closely related are Lerner (1999) and Howell (2017), who study the real and financial impacts of government grants in the form of Small Business Innovation Research (SBIR) on startups. Lerner (1999) argues SBIR funding plays a certification role by conveying information about a startup's quality to VCs. Howell (2017), on the other hand, finds that initial Phase I SBIR funding enables prototyping, which reduces investor uncertainty. 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, Bai, Bernstein, Dev, and Lerner (2021) propose that public-private co-investments are effective when the government invests in earlier-stage projects. Similarly, Akcigit, Hanley, and Serrano-Velarde (2020) propose that the government's funding targeted at basic research is welfare-improving, whereas subsidizing applied research, which the private sector could otherwise finance, is less effective. Consistent with this view, our results show that public funding of basic science supplies a public good that is essential for scientific entrepreneurship.

Babina, He, Howell, Perlman, and Staudt (2023) is another related study. Consistent with our results on academic startups and inventors, they find that public funding of university research enables academic entrepreneurship. Our key contribution to this literature is showing a coordinated program aimed at resolving a major technological bottleneck can

[17]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).

crowd in VC investments.

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).[18] Up to that point, to understand neural activity, neuroscientists were using electrodes that sparsely sampled brain activity, typically capturing signals from one to a few neurons in a specific region. The article argues that understanding neural circuits, which can involve millions of neurons, requires observation at a multi-neuronal level, as single-neuron recordings are insufficient—akin to trying to understand an HDTV program by focusing on just one or a few pixels on the screen. The article suggests a large-scale effort to map neural circuits could lead to a major scientific breakthroughs:

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

These ideas were formally consolidated into an action-based proposal, published in Science[19] 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)

[18] 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.

[19] Alivisatos et al. (2013)

and Modic and Feldman (2017) provide a detailed comparison of their backgrounds and differences. The overarching goal of the BI is to map the human brain, while HBP's goal was far more ambitious to simulate the human brain, which many found unrealistic. BI was rooted in the interactions and consensus of a wider neuroscience community, while HBP was an initiative led by a few neuroscientists. This highlights the importance of consensus decision-making in setting the mission for such programs. Additionally, the process leading to the BRAIN Initiative's designation as a *Grand Challenge* in the US was more transparent than its European counterpart. Consequently, the BRAIN Initiative quickly gained popularity within the US neuroscience research community, while the HBP faced considerable controversy in the EU. In 2014, 750 European researchers signed an open letter to the European Commission criticizing the HBP's overly narrow focus and threatening to boycott the project (Guardian, 2014). Although the HBP continued until 2023, it appears to have had minimal impact on the European neuroscience community (Atlantic, 2019), whereas the BI, which is set to end in 2026, has already been applauded by the neuroscience community (Nature, 2021).

Initially, the funding level for the BI was announced at \$4.5 billion over a period of 12 years (NIH, 2014b). Based on agency budget reports, grant data, and BI fact sheets, we estimate that the US government has invested over \$4.8 billion in basic neuroscience research between 2014 and 2022. While multiple government agencies, including NSF, DARPA, IARPA, FDA and Department of Energy were involved in the initiative, not all of them were active funders.[20] Details on annual funding levels by the agency are provided in Appendix A. NIH is the leading and central agency with 62% of the total funding with a working group that actively coordinates and evaluates the program.

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

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

engineering, and computer and information sciences. These distinct features set the program apart from previous neuroscience grants.

Beyond its direct scientific contributions, the BI has spurred the development of critical research infrastructure and resources. The foundational proposal published in Science acknowledges that achieving the goal of mapping the brain *"...require developing methods for storing, managing, and sharing large-scale imaging and physiology data, as well as developing methods for analyzing data and modeling underlying neuronal circuits, leading to emergent principles of brain function. It will be carried out by providing access to all investigators, including cellular, systems, and computational neuroscientists, to the methods and data needed for developing, testing, and verifying theories of how the brain operates."* In line with this direction, BI has contributed the development of new tools for capturing brain activity data and platforms for openly disseminating this data. For instance, Google Research has collaborated closely with BI scientists to develop computational tools for managing one of the BI datasets, sized at 25K terabytes (Januszewski, 2023). Also, BI's open-source data-sharing policy mandates awardees to disseminate their data on designated BI data archives, promoting knowledge spillover (NIH, 2019) within the neuroscience community and outside.

3. Sample and Data

Our dataset consists of information on VC-backed startups, their innovation, personnel, financing events, and NIH and NSF research grants. We begin with the universe of VC deals from Pitchbook to identify startups that are backed by VC, collecting detailed information on round sizes, number of rounds, pre-money valuation, and exit outcomes of VC investments (Section 3.1). For these VC-backed startups, we construct their patent portfolios using data from PatentsView and Ewens and Marx (2023) (Section 3.2), as well as their employee information from the LinkedIn dataset (Section 3.5). We further incorporate research grant data from NIH and NSF and link the resulting publications from these grants to Scopus for detailed information on these publications (Section 3.4). Finally, we identify *Neuro startups* by examining the patent portfolios of these startups (Section 3.3).

3.1. VC-backed startups

Our study focuses on US startups that received their first VC funding between 2000 and 2019 from Pitchbook.[21] We start our sample in 2000, the year Pitchbook became more reliable. Our sample ends in 2019, the last year before the COVID-19 pandemic, since public and private funding shifted towards COVID-19 treatment and vaccine R&D thereafter, potentially introducing confounding factors into our analysis. Our final dataset

[21] US startups are startups headquartered in the US

contains 50,601 startups founded between 1990 to 2019. These startups operate in 40 unique primary industry groups, with 65.02% concentrated in just five of them. These five leading industry groups are Software, Commercial Services, Pharmaceuticals and Biotechnology, Healthcare Devices and Supplies, and Media, accounting for 37.22%, 10.35%, 7.65%, 5.74%, and 4.05% of the total number of VC-backed startups, respectively.

For a financing round to be considered in our study, it must involve a new equity issuance,[22] and be classified as a "Venture Capital" round in the Pitchbook dataset.[23] Our final dataset contains 94,565 unique financing deals with non-missing values in round sizes. Table 1 shows the first financing round has an average round size of $4.57m at a pre-money valuation of $12.78m. When considering all financing rounds, the average round size goes up to $9.93m, alongside a pre-money valuation of $80.51m. This is unsurprising, as later stages of VC rounds generally have larger round sizes and higher pre-money valuations than the first round. The distribution of both round size and pre-money valuations is highly right-skewed. The number of VCs per deal averages 1.77 in the first round, rising to 2.17 in later rounds.

Besides, we track exit outcomes of VC investments through 2022 to evaluate the success of each VC investment in a startup. 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 a value of zero for these startups. For this group, we follow Ewens and Sosyura (2023) and use the beta distribution to assign a failure/exit date between 2 and 5 years after the last financing event.

3.2. Innovation

To construct the patent portfolios of startups, we link Pitchbook data to PatentsView and augment our dataset with 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.[24] We employ a two-stage process to link PatentsView with Pitch-

[22] We exclude rounds consisting solely of debt or secondary sales

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

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

book. In the first stage, we use the name-matching algorithm described in Tumarkin (2020) to identify the closest matching patent assignee names for each startup's legal name. We rely on the startup's legal name and the assignee names on patents because the legal name serves as the formal identifier of a startup, while the assignee represents the legal owner of the patent rights. Recognizing the possibility of closely similar names among different entities, the second stage compares the location of the patent assignee with the startup headquarters at the state level. A patent is considered linked to a startup if the patent assignee and the startup match on both name and location.

Furthermore, we cross-verify our dataset against the comprehensive patent dataset from Ewens and Marx (2023), which details the founding years for 85% of US-based assignees in PatentsView and identifies VC-backed startups. To conduct this comparison, we collect all patents from organizations classified as VC-backed in Ewens and Marx (2023) and note that a reasonable portion of organization names in Ewens and Marx (2023) exactly match the legal names in Pitchbook. However, some organization names are not the legal names of startups in Pitchbook. To ensure accuracy and minimize measurement errors, we opt not to use fuzzy matching for all startups in Ewens and Marx (2023) against Pitchbook. Instead, we directly merge our data with Ewens and Marx (2023)'s based on exact matches between organization names in their dataset and legal names in Pitchbook, focusing on startups with identical names in both sources. If our dataset contains a similar number of patents per startup as the dataset in Ewens and Marx (2023), our matching quality should be considered comparable. Our comparison shows an average difference of 1.86 patents per startup, with a maximum difference of 23 patents, suggesting that our matching procedure is reasonably accurate, especially given that we are using a different version of PatentsView. To refine our dataset's precision, we create a combined set of patents from both our dataset and Ewens and Marx (2023)'s. In our sample, 9,790 startups possess at least one patent, with an average of 12.91 patents per startup.

Besides, our study uses the Artificial Intelligence Patent Dataset (AIPD) constructed by Giczy, Pairolero, and Toole (2022) to identify patents containing AI-related components. 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, which are important because claims define the legal scope of the invention (Giczy et al., 2022).

3.3. Neurotech

To identify the neurotech space, we rely on patent data. This approach has several advantages. First, patents represent economically valuable innovations that grant exclusive legal rights to their owners (Hall, Helmers, Rogers, and Sena, 2014), and provide time-stamped records of a firm's innovation activities. Second, patent data are available for not only VC-backed startups but also for all patenting firms and startups across the economy, allowing us to analyze non-VC-backed startups. Third, there is no standard industry classification (such as SIC, NAICS, or in Pitchbook) that reliably identifies neurotech startups.[25]

3.3.1. Neuro Patents and similar technologies

Before determining patents with neuroscience components, we first need to identify the relevant keywords for neuro-related technologies, which we refer to as *Neuro keywords* hereafter. We obtain *Neuro keywords* through the following three steps. First, we collect all Pitchbook keywords that describe the business operations of startups and contain *neuro* or *brain*, resulting in a list of approximately 500 keywords. [26] Next, we use ChatGPT and consult with a neuroscience researcher to rank these keywords based on their relevance to neuroscience. Lastly, we manually check and filter out keywords that introduce noise.[27] Our final set of *Neuro keywords* includes *neuro, nerve, brain, optogenetic, Parkinson, Alzheimer, dementia*.

Furthermore, we identify the *neuro-related CPC technology group* by searching for *Neuro keywords* in the titles of the CPC technology group. The CPC technology group is the most granular level of CPC classification, allowing us to capture neurotechnology with greater specificity. In total, we identify 220 *neuro-related CPC technology groups*.[28] G06F3/015 is one example of a *neuro-related CPC technology groups*, with the following title: *Input arrangements for transferring data to be processed into a form capable of being handled by the computer; Output arrangements for transferring data from processing unit to output unit, e.g. interface arrangements-Input arrangements or combined input and output arrangements for interaction between user and computer -Arrangements for interaction with the human body, e.g. for user immersion in virtual reality -Input arrangements based on nervous system activity detection, e.g. brain waves [EEG] detection, electromyograms [EMG] detection,*

[25] In more recent versions of Pitchbook, which were not available to us, "neurotechnology" is listed as an emerging category.

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

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

[28] We use CPC classifications rather than raw patent text because CPC provides standardized terminology, ensuring consistent identification of neuro-related patents.

electrodermal response detection

We identify patents with neuroscience components as patents in the *neuro-related CPC technology group* and refer to these patents as *Neuro Patents* hereafter. To find similar comparable technologies for *Neuro Patents*, we rely on CPC technology subclasses, the second most granular level of CPC technology classification. The first four characters of a technology group identify its subclass. For example, in the CPC technology group G06F3/015, the corresponding subclass is G06F, which represents *Electric Digital Data Processing*. A CPC technology subclass often contains multiple CPC technology groups and may include both neuro-related and non-neuro-related groups. As a result, we define patents in technologies comparable to neurotech as those classified in non-neuro-related technology groups but within the same subclass as *Neuro Patents*.

3.3.2. Neuro Startups

We define a startup as a *Neuro startup* if it has at least one *Neuro Patent*. The validity of this definition relies on the assumption that a startup's patenting activity reflects its primary business operations. This assumption is reasonable because startups usually have a narrow technological focus and a limited number of products due to their constrained resources. Besides, Patents are likely to be key assets for startups, as they often represent economically valuable innovations with exclusive commercialization rights. Our sample contains 755 *Neuro Startups*, which form the treated group and collectively hold 1,841 *Neuro Patents*. Among these startups, 88% operate in the healthcare sector and 8% in the IT sector. Our sample includes well-known *Neuro Startups* such as Neuralink, Lumos Labs, and Neurotrack Technologies, all of which have received significant media attention.

Furthermore, we exclude firms that obtain their first *Neuro Patents* after a VC exit, as these firms are typically larger and tend to hold patents across diversified technology areas following the exit. Our results are robust to a more rigorous definition of *Neuro startups* that captures patent timing. Under this definition, a *Neuro startup* must file for a patent in a five-year window after the first VC round. The limitation of this definition is that we might lose startups whose R&D have longer timelines or those that choose to reveal their IP through patents later in their life cycle.

As an alternative classification of *Neuro startups*, we also consider relying directly on Pitchbook's business descriptions or keywords provided by Pitchbook. While the findings using the classification are consistent with the patent-based definition, we prefer the patent portfolio approach because the business description keywords are subject to Pitchbook's information, the source of which is unknown to us. Our comparison of different versions of Pitchbook reveals that a startup's description slightly varies over time. This could be problematic if startups self-select to describe themselves with fashionable words. We do not face such limitations when using patents, as they provide a reliable timestamp of a startup's underlying technology, and their technological classifications are reviewed by domain technology professionals.

3.4. Research grants

We gather detailed information on NIH and NSF BI grants and non-BI neuroscience grants from NIH, following the process described in Appendix 6 and **??**. Our study focuses on NIH and NSF grants, because these two agencies provide the lion's share of funding, with NIH providing significantly more. Besides, NIH and NSF also offer more detailed grant-level data than other funding agencies. Collectively, NIH and NSF allocated \$4.3 billion and an average of \$1.1 million per project from 2014 to 2022. The majority of these research grants produced scientific publications. More specifically, 82% of NIH-funded projects resulted in publications, yielding 7,448 unique outputs. Meanwhile, the NSF's 694 BI grants led to 6,138 publications. Besides, we collect additional details such as titles, citation counts, publication years, authors' names, and affiliations from Scopus (Rose and Kitchin, 2019), enhancing our dataset with this comprehensive information.

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

3.5. Startup Employees

Our goal is to collect detailed information on each startup's employees, including their resumes from the LinkedIn dataset, their patent portfolios from PatentsView, and whether they are authors of BI-funded publications. To achieve this, we integrate these three datasets at the individual level. More specifically, we first identify Pitchbook startups in the LinkedIn dataset. The LinkedIn dataset and its linkage to Pitchbook startups are developed by Revelio Labs. In our sample, we can identify 80% of all startups and 86.48% of all Neuro startups in the LinkedIn dataset. The employees of these matched startups constitute our base dataset.

For each employee in this base, we collect information on their name, employment history, and position within the firm.

Next, we query the author identifiers of BI publications using the DOI or PMID of each publication through Scopus. These Scopus author identifiers allow us to collect each author's names, areas of expertise, affiliation history, and publication records. We link startups' employees and BI publication authors using their names and employee history. A match is confirmed when two individuals share similar names and have overlapping employment histories, as detailed in Masulis and Yao (2025).

To identify the patent portfolios of startup employees, we collect inventors' names and their assignee histories from PatentsView. We consider that inventors' assignee histories reflect their employment history, as assignees are the legal owners of the underlying patents. We then follow the same two-stage procedure described in Masulis and Yao (2025) to link startup employees with inventors. We identify 60,371 startup employees as inventors and 2,983 employees as co-authors of BI grant-derived publications.

3.5.1. Academic Startups and Inventors

We identify a startup as an *Academic Startup* if it has at least one senior employee with an academic background within the three years after being founded. We focus on senior employees because they often play managerial roles and are more likely to influence the startup's innovation and business strategy with their scientific knowledge. We define a senior position based on Revelio's seniority level, categorizing positions with a seniority level above 5 (on a scale from 0 to 7) as senior roles.[29] We define an employee as having an academic background if this employee who holds a PhD in STEM and has worked at an academic institution under job titles such as {*professor, graduate, lecturer, academic, researcher, faculty, dean, instructor, scholar, scientist, postdoc, PhD, doctor, researcher, fellow, educator*} Additionally, we identify academic institutes based on whether the employer's name include keywords such as "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." Additionally, using the startup inventors identified in Section 3.5, we define, we define *Academic Inventors* using the same criteria applied to identify *Academic Startup*.

4. Validity of the BRAIN Initiative as a Shock

For a causal interpretation of our DiD analysis, the parallel trends assumption needs to hold. This requires that, absent the shock, the relative changes in the treated group would not have occurred. We cannot formally prove this, but we provide evidence in line

[29] For example, these roles include founders, CEO, and VPs.

with it. We first show that public markets positively reacted to the announcement of the BI in anticipation of its commercial impact. Next, we show that these anticipations were not unwarranted. By analyzing scientific output, we show that BI significantly advanced the commercialization of neuroscience. In the next section, where we discuss the main results, we provide dynamic DiD estimates that rule out the existence of a pre-trend in VC investments.

4.1. Public Market Reaction to the BI

A typical concern with a DiD analysis is that the shock might capture an omitted variable. In our setting, a serious omitted variable could be other pre-existing breakthroughs in neuroscience, which may have elevated the expected return on neurotech investments. Such breakthroughs may even have primed the government to initiate its program and therefore join an already booming field. Anecdotal evidence contrast with this story; leading up to the BI, even pharmaceutical companies, traditionally major investors in neuroscience R&D, were cutting their expenditures in the field due to high uncertainty and failure rates (Miller, 2010; Nutt, 2011; Insel and Landis, 2013; Choi et al., 2014).

We formally test this story by focusing on a narrow window around BI's announcement. While our focus is on private entrepreneurial firms, the richer information set on publicly traded companies allows us to investigate how capital markets reacted to the BI. We cannot simply examine the stock price reactions of large pharmaceutical companies, because they often pursue R&D in multiple areas, with neuroscience representing only one. Instead, we leverage patent valuation data developed by Kogan et al. (2017), which closely ties a particular technological innovation to its valuation. We isolate the BI's impact by examining the cross-sectional variation in the valuation of *Neuro patents* compared to patents in similar technologies. A reduction in technical uncertainty as a result of the BI should raise the valuation of innovation in the field only after its announcement. In contrast, if the field was already booming independently, the BI announcement should have elicited a minimal market response in a short window. Conducting this analysis at the VC funding level is not feasible because (i) we do not observe a sufficient number of VC financing events in a short window around BI's announcement (ii) we cannot estimate patent valuate for private firms.

Our analysis includes patents granted within one- and two-year windows surrounding the BI announcement. On April 2, 2013, President Obama publicly announced the BRAIN Initiative. This is our baseline treatment date. Our cross-sectional difference-in-difference regression estimates the following equation at the patent level:

$$Y_{it} = \beta_1 \text{NeuroPat}_i \times \text{Post}_t + \beta_2 \text{NeuroPat}_i + \beta_3 \text{Post}_t + X_i + \upsilon_{it} \quad (1)$$

where Y is the logarithm of the patents' market value or the number of citations for patent i, granted on date t. NeuroPat$_i$ is an indicator with the value of one for neuroscience patents or zero for similar technologies, as defined in Section 3.3.1. Post$_t$ equals one if the patent is granted after 2nd April 2013 and 0. The key coefficient of interest is (β_1), which is the interaction between *NeuroPat* and *Post*. X is a vector of patent controls, including firm and filing year fixed effects. Filing year fixed effects help us isolate technological waves that might be correlated with the value of innovation. This specification allows us to compare patents filed by the same firm, in the same period, where a key difference is a plausibly exogenous variation in grant date–i.e., before or after the BI's announcement.[30] We cluster standard errors at the treatment, i.e., patent subclass, level.

We present the results of the OLS regression of Equation 1 in Table 2, where all tables include neuro and similar patents of public firms. The sample in Columns (1-2) includes patents granted in 2012 and 2013. Firm and filing year fixed effects are included in Column 1. In Column 2, we include filing year $\times$ firm fixed effects to absorb the dynamics of innovation within the same firm. In Columns (3-6), we exclude the interval between President Obama's State of the Union Address on February 12, 2013, and the official BI announcement on April 2, 2013. In his State of the Union speech, the President briefly hinted at plans to invest in mapping the human brain, potentially signaling the initiative to the market. However, the formal and more specific announcement occurred on April 2. Accordingly, in Columns (3) and (4), we exclude these dates and include one year before and after them. In Columns (5) and (6) we extend this to two years before and after. We choose a one-year and two-year interval around the announcement date as a reasonably short sample. A shorter interval comes at the cost of losing statistical power, especially variation at the treatment, i.e., patent, level.[31]

The coefficient on $NeuroPat \times Post$ captures the average changes in patent values from pre- to post-BI for neuroscience patents relative to the change for other similar patents within the same firm and filing year. All β_1 coefficients are positive and statistically significant at the 1% level. More specifically, the β_1 of column 1 is 0.122, suggesting that the market's valuation of *Neuro patents* increased by 12.2% relative to similar patents after the BI's announcement. Using the longer window of 2 years in column 5, we observe a larger coefficient of 0.314, indicating a 31% increase increase in this valuation. Also, note that the coefficients of $NeuroPat$ are consistently negative and statistically significant across the columns. This

[30] The average (median) lag between a patent's filing date and grant date in this sample is 1296 (1187) days. It is implausible that firms strategically file certain patents three to four years before the BI, in anticipation of its announcement.

[31] For example, if in the symmetric sample (Columns 3-6) around the shock, we restrict our sample to 30 days before and after, we will only have 156 *Neuro patents*, whereas in a one year window this number is 2363. Note that our study is cross-sectional at the patent level.

suggests that *Neuro patents* were valued lower than their peers pre-BI, which is consistent with the anecdotal evidence on high failure rates in the field as mentioned above.

An alternative explanation is that this upward valuation adjustment reflects the inherent quality of these patents rather than the BI news. That is, *Neuro patents* granted right after the BI coincidentally had higher qualities. To examine this, we replace patent value with the number of patent citations it receives, as a more direct measure of technological quality, and re-estimate Equation 1. We use a Poisson estimator this time because the outcome is a count variable with many zeros (Cohn, Liu, and Wardlaw, 2022). The results are reported in Panel B of Table 2. Contrary to this story, the coefficients on $NeuroPat \times Post$ are statistically insignificant, indicating no change in patent quality post-BI, while the coefficients on $NeuroPat$ are negative and statistically significant. Again, this is consistent with the anecdotal evidence that neurotech innovation was struggling in a close interval before the announcement of the BI. Overall, these results suggest that markets improved their valuation of neurotech innovation in a short interval after the announcement of the BI. The timing of this adjustment, in a setting other than venture capital, motivates our use of BI as a shock.

4.2. Scientific Output of the BRAIN Initiative Science

The results above show the ex ante effect of BI: markets quickly reacted to the BI's announcement, while no real scientific output was produced. Now, we study whether the BI's output met these expectations by advancing the commercialization of neuroscience ex post. Two primary channels for this are supplying open science and skilled labor.[32] In later sections, we expand on the labor channel. Here, our focus is on measuring the commercial impact of BI-funded publications. We use three measures for this purpose. These measures build on the idea that academic publications are more commercially impactful when they influence follow-on patents. As such, our first measure uses Reliance on Science data by Marx and Fuegi (2020, 2022) and counts the number of patents citing an academic article. The second measure, developed by Masclans et al. (2024), predicts the commercial potential of an academic article as its probability of being cited by a renewed patent. We then compare these impact measures with those of other publications in neuroscience that are funded by NIH but are not part of the BI.[33] We refer to the latter group as *non-BI neuroscience*. This group is a close benchmark that not only controls for unique features of the field but also for research funded by the main public agency behind the BI.[34] The results and discussion in

[32] university-based IP is also important, but we cannot observe university licensing contracts.

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

[34] For example, medical research publications generally receive more citations than those in other disciplines. Or, the availability of funding across different fields can affect their commercialization.

Appendix C and Table A3 show that BI-funded publications on average receive four times more citations compared to non-BI neuroscience and have higher commercial potential as predicted by the Masclans et al. (2024) measure.

Nonetheless, direct citations are likely to underestimate BI's impact for two reasons. First, the BRAIN Initiative occurred in the recent half of our sample, which causes the truncation issue with patent citations (Lerner and Seru, 2021). For example, Lerner, Manley, Stein, and Williams (2024) find that it takes 3.7 years for a publication to receive its first citation by a patent. The second issue, perhaps more important, is that relying on citation paper trails overlooks a significant amount of spillovers (Myers and Lanahan, 2022). This is exacerbated in our setting due to the imperfect appropriability of basic science. Patents tend to cite prior art immediately related to the invention, which implies the broader scientific foundation, open data, tools and methods used in the invention process are less frequently cited. USPTO's chief economist argues that machine learning is a powerful tool to overcome these limitations (Toole et al., 2020). We therefore develop a large language model (LLM) to identify *Neuro patents* that are influenced by the BI publications. Our LLM is a SciBERT,[35] which is well equipped to understand scientific text. We fine-tune the model to calculate a score between 0 and 1 to measure BI's influence on a given patent. To avoid a look-ahead bias, we develop a separate model for every year from 2015 to 2020, such that the patents are only influenced by the knowledge generated up to that point. For example, a patent in 2017 cannot be influenced by the knowledge generated in 2018.

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

We further divide our labeled sample into three sets: 80% for training, 10% for testing, and 10% for validation. We report the model performance in Table A4. All other models achieve a weighted average F1-Score above 0.9, which shows high accuracy for the model's predictions. In addition to conventional machine learning performance metrics, we also validate the performance of our model using patent citations. We test whether our model

[35] A BERT model trained on 1.14M scientific articles (Devlin et al., 2018)

can predict patents that directly cite BI publications as patents influenced by BI research. Our model correctly predicts that 87.54% of these patents are influenced by BI research. Using our trained model, we find that 66% of *Neuro patents* of VC-backed startups in our sample are influenced by BI research.

5. Main Results

5.1. Probability of Raising Venture Capital

Our first hypothesis is that the government's commitment to mapping the human brain—via the BRAIN Initiative—crowds in venture capital. Securing VC funding is a key milestone for high-growth startups. According to Gompers et al. (2020), VCs reject roughly 100 firms for every one they decide to fund, meaning the vast majority of startups seeking VC never receive it. This is especially the case in emerging fields like neurotech, where the commercialization path is more uncertain. Thus, if the BI made *Neuro startups* more attractive to investors, we would expect an increase in their likelihood of raising VC.

Testing this requires identifying startups in the economy in the neuro space and studying whether their probability of raising VC increases compared to a control group. We use patent data to determine a startup's technological focus. Also, firms that have filed for patents have demonstrated technological innovation, and their IP protection makes them plausible candidates for VC funding. Ewens and Marx (2023) provide data on the founding year of US companies that have ever filed a patent. By drawing from this universe, we can identify both *Neuro startups* and the control group regardless of whether they have raised external capital. We restrict our sample to firms founded and filing for their first patent between 2000 and 2019. The control group consists of young firms with patents in similar technologies, *SimilarTech startups*, as defined in Section 3.3.1. Our analysis compares the probability of a *Neuro startup* raising VC before and after the BI relative to the control group. We estimate the following panel regression:

$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t \ + \beta_2 Ln(FirmAge)_{it} + \lambda_i + \tau_t + \upsilon_{it} \tag{2}$$

where Y_{it} equals one if the startup i has ever raised VC up to year t and zero, otherwise. Neuro is an indicator for whether the startup is a *Neuro startup* as defined in Section 3.3. *Ln(Firm Age)* is the log-transformed difference between year t and the startup's founding year. λ controls for firm fixed effects and τ controls for year fixed effects. A startup enters the panel in its founding year.

Table 3 reports the results of this estimation and shows that *Neuro startups* are more likely to receive VC funding than other startups with similar technologies. Columns (1-2) include data from the entire sample period, whereas Columns (3-4) focus on a five-year window before and after the BI. The age of a startup could be positively correlated with the likelihood of receiving VC funding, for example, due to the firm's maturity. Thus, we include *Ln(Firm Age)* in Columns (2) and (4). All coefficients of $Neuro \times Post$ in Table 3 range from 0.015 to 0.023 and are statistically significant. The results 3 suggest that *Neuro startups* have an additional 1.5 to 2.3 percentage points higher likelihood of receiving VC compared to other similar firms post-BI.

For consistency with the rest of our analyses in the paper, which can only be estimated cross-sectionally based on observed VC investments, in Appendix D and Table A5 we conduct a cross-sectional analysis on the extensive margin. The focus of this analysis is whether startups that have a *Neuro patent* in the first three years after being founded, or three years after their first patent, can also raise VC in the same three-year period. This also addresses the over-representation of older startups in a panel setting. The results are directionally and statistically similar to the panel structure.

5.2. *Intensive Margin: VC Investments, Financing and Valuation*

The previous analysis shows that post-BI, the relative likelihood of receiving venture capital for *Neuro startups* increases. In the rest of the paper, we condition our analysis on startups that receive VC. The VC's common practice of stage-by-stage financing is explained as a real abandonment option that enables VCs to address entrepreneurial uncertainty. Staging, characterized by smaller financing rounds instead of one upfront capital injection, helps VCs collect information on the startup's progress and reduce their exposure to the startup's failure risk (Gompers, 1995; Cornelli and Yosha, 2003; Bergemann and Hege, 2005; Ewens et al., 2018). In our setting, with a reduction in uncertainty, we should expect a relaxation in staging and therefore larger financing rounds. Similarly, this reduction should also lower the discount rate that VCs use in their valuation and therefore increase the project's net present value. We take these hypotheses to the data by examining the size and valuation of VC financing rounds for *Neuro startups* compared to other startups–and more refined control groups–they fund. For this test, we estimate the following equation at the financing round level:

$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t + \beta_2 X_{it} + \tau_t + \upsilon_{ijt}, \tag{3}$$

where X_{it} are entrepreneurial firm characteristics at the time of the investment, including industry group fixed effects, geographic fixed effects, logged-transformed number of investors in the round, and an indicator for whether the firm was a *Neuro* startup (i.e., treated), τ_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*. Pitchbook offers three levels of industry classification, with the broadest being the industry sector (akin to SIC2), followed by an industry group (akin to SIC3) and an industry code (akin to SIC4). Healthcare is one of seven industry sectors and is the second largest in terms of number of VC-backed companies after IT.[36] Our industry fixed effects are at the more granular level of industry groups.[37]

The baseline control group comprises all non-Neuro VC-backed startups. This group provides a broad comparison between *Neuro startups* and high growth startups in diverse sectors that VCs fund. To further enhance the comparability, our second and most relevant control group are VC-backed startups within the Healthcare sector. This sector, primarily composed of life science companies, is inherently research-intensive and, like the neuro segment, relies heavily on scientific breakthroughs and developments. Hence, startups in this sector can serve as a more relevant benchmark when assessing the unique impact of public funding on *Neuro startups*.

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

In Panel A of Table 4, we report the results of the OLS regression of Equation 3. The outcome variable, first round size, is log transformed to account for its skewness. We include year, state, and industry group fixed effects. In our specifications, we also control for the number of VCs that are active in the funding to control for the fact that a larger syndicate can provide larger funding amounts. In Column (1), we include all VC-backed startups in the sample. In Column (2), we limit the sample to startups in the healthcare sector, which offers a closer control group. In Columns (3) and (4), we focus on the round size of all rounds. To address the concern that round sizes are positively correlated with round numbers, we

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

[37]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.

include fixed effects for VC round numbers to compare round sizes within the same round.

The $Neuro \times Post$ interaction term, which captures the incremental effect on *Neuro startups* post-BI, is significantly positive across all specifications. Specifically, when focusing on first-round VC investment, the coefficient ranges from 0.494 in the overall sample to 0.392 within the healthcare sector. These coefficients suggest that ceteris paribus, *Neuro startups* have seen an increase in the amount of first-round financing by approximately 39.2% compared to other patenting startups in the healthcare—which offer the closest control group to *Neuro startups*— to 49.4% compared to all other startups, post-BI. This result is statistically significant at the 1% level. Columns (3) and (4) present the regression results where the outcome variables are round size across all financing rounds. The coefficients of $Neuro \times Post$ are 0.278 in the overall sample and 0.213 within the healthcare sector, and statistically significant at the 1% level. For example, column (4) suggests that, post-BI, *Neuro startups* experience a 21.3% increase in VC investment amounts relative to other similar VC-backed startups in the healthcare sector at the same stage of financing.

While these results show that VCs make larger investments in *Neuro startups*, it does not necessarily mean the underlying science is of more value in the eye of the markets. It could be that due to changes in R&D costs, *Neuro startups* have larger capital requirements to finance their operations. As such, we next turn to valuations, which also reflect the uncertainty associated with neurotechnologies. In Panel B of Table 4, we report the results from OLS regressions, paralleling the structure used for analyzing financing size, but this time focusing on the pre-money valuations; i.e., valuation at the financing event net of the VC's investment amount. Again, we employ log transformation to mitigate the impact of skewness. The $Neuro \times Post$ interaction term is significantly positive, indicating a robust post-BI increase in the valuations of *Neuro startups* across the first financing rounds. Specifically, Panel B shows that first-round financing post-BI sees valuation increases between 41.6% in the healthcare sector and 36.3% across the overall sample. This significant uplift, noted at the 1% levels, highlights the BI's strong influence on enhancing the perceived value of *Neuro startups*. When considering the pre-money valuation for all rounds, the coefficients of $Neuro{\times}Post$ are positive and statistically significant at the 1% level, as described in Columns (3) and (4) of Panel B. Following the BI, the valuations of *Neuro startups* increase by 23.7% and 23.5% relative to other VC-backed startups and VC-backed startups in the healthcare sector, respectively. These valuation increases post-BI for *Neuro startups* are pivotal as they not only indicate an augmented investment scale but also reflect market sentiment regarding the potential and reduced technology uncertainty associated with these startups. A higher valuation typically denotes greater market confidence, likely stemming from advancements in basic science funded by initiatives like the BI. This enhanced confidence could be due to the BI's role in reducing the R&D uncertainty, offering more robust scientific foundations for *Neuro startups*, and increasing the attractiveness of these ventures to VCs.

5.2.1. Parallel trend Assumption of the 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 the outcome of the treated and control units would have changed by the same amount without the treatment. Figure 3 shows the time series of VC financing for both Neuro and non-Neuro startups. For the assumption of parallel trends to hold, the paths of the Neuro and non-Neuro groups should not display systematic differences before the shock. In the graph, the two lines representing *Neuro* and *non-Neuro* startups appear to move similarly before the vertical line denoting the BI in 2013, suggesting that before the BI, the financing size and valuation were trending similarly for both groups. After the BI, however, there is a strong divergence, with Neuro startups receiving larger financing and at higher valuations than non-neuro startups. This divergence after the BI is consistent with the treatment effect we aim to measure.

We also estimate the dynamic version of Equation 3, replacing *Post* with year dummies. Figure 4 shows the coefficients where the control group is all other startups in the healthcare sector. footnote We repeat this exercise for all rounds and plot the estimates in Figure A.1. We keep a balanced sample seven years before and after the shock. The patterns in the figure show that there is no pre-trend and that the timing of the increase in financing amounts and valuation is consistent with the announcement of the BRAIN Initiative. There is indeed a significant spike in financing outcomes in 2013, while BI has not yet had any immediate scientific outputs. This surge can be explained by the elevated perceived upside potential of these firms. The BI likely acted as a strong signal of government commitment and potential future breakthroughs. VCs, who invest based on the future option value of their investments, could anticipate significant scientific advancements and commercial opportunities stemming from increased funding, regulatory support, and collaboration between academia, industry, and government.

5.2.2. Alternative Control Groups

Healthcare startups provide the closest control group for *Neuro startups* due to their R&D projects having a long-term nature with low demand uncertainty. Nevertheless, we examine three alternative control groups to ensure the robustness of our findings, which are

Cancer startups, *Patent startups*, and *SimilarTech startups*.

Cancer startups are startups classified under Pitchbook's Oncology vertical. This vertical, typically a subset of healthcare, comprises startups focused on developing cancer treatment. Similar to Alzheimer's, Parkinson's, and dementia, there is a significant market for cancer treatments, without an effective solution. Cancer R&D also faces high technical uncertainty and relies on basic science.[38] Consequently, in 2016, the US government launched a mission-oriented program, the Cancer Moonshot, to advance cancer R&D. This renders startups in the Oncology vertical as a close control group to *Neuro startups*, except for the timing of the government's intervention. We exploit the lag between the introduction of the BI and Cancer Moonshot to see if VC investments react to neurotech but not Oncology. We study the three years after BI's introduction and before the Cancer Moonshot (2013-2015) as the post period and the three years before as the pre-period (2010 to 2012). We address this by excluding startups that are both in Oncology and neuro from this analysis.[39]

The second alternative control group is *Patent startups*, which are startups that hold at least one patent during the VC investment period. Patent activity is a broad proxy that distinguishes scientific startups from the service-as-a-software (SaaS) and IT startups and helps address the concern that patenting activity may positively influence financing outcomes. A subset of *Patent startups* is our third control group: *SimilarTech startups*. These are startups with at least one patent in a technology class similar to neurotechnology, as outlined in Section 3.3.1.

Table A8 replicates the analysis in Table 4 using these three alternative control groups. When considering only the first round, all coefficients on $Neuro \times Post$ are positive and statistically significant at the 5% level or better. The economic magnitude is largest when *Cancer startups* is a control group. More specifically, table A8 shows that, post-BI, *Neuro startups* receive 48.2% larger first round investment and have 46.6% higher first round pre-money valuation relative to *Cancer startups*. When considering VC investments across all rounds, all coefficients are positive. However, only the specification using *Patent startups* as the control group is statistically significant. In this case, *Neuro startups* receive 14.5% more investment relative to other *Patent startups* post-BI.

5.2.3. Alternative Classification of Neuro startups

Relying solely on patents may cause us to overlook *Neuro startups* that never file for a patent. To address this issue, we use Pitchbook's descriptions to identify *Neuro startups*

[38] Cancer research involves many disciplines such as genetic mutations, cellular signalling pathways, and immune interactions. Also, cancer research heavily relies on the breakthroughs in molecular biology, genetics, and immunology.

[39] A caveat with this group is the spillovers and complementarities between the R&D in these two areas, which restricts us from using it as the main control group.

based on the same set of keywords. The classification process is detailed in Section 3.3. In the Appendix Table A11, we replicate the analysis from Table 4, and our results remain consistent. This approach also alleviates concerns about look-ahead bias.

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

Nevertheless, in Appendix Table A10, we revisit the results from Table 4 by defining a *Neuro startups* as a firm that files for a neuro patent within the first five years after its founding. Our results still hold for this sample. The advantage of our baseline classification is that, by not narrowing the classification timeline, we avoid excluding startups whose R&D takes longer to reach the patenting stage. Moreover, using patents over Pitchbook's descriptions has the benefit of relying on legal documents that have been verified by examiners. While Pitchbook descriptions are generally informative, we believe patents are superior in our context.

5.2.4. Exposure to the BRAIN Initiative

Thus far, our results show that post-BI *Neuro startups* became more attractive for VC investments relative to the control group. To show a more direct link between the BI as the source of this elevated attraction, we exploit the heterogeneity of *Neuro startups* in their exposure to the BI. We measure this exposure through three separate proxies: 1) labor exposure as observed through hiring BI-funded researchers 2) IP exposure as observed through patents that use BI-generated knowledge and tools 3) geographical exposure via proximity to BI-funded institutions.

If BI is indeed driving the elevated VC interest in neurotech, then within the *Neuro startup* group, firms with greater BI exposure should secure even better financing outcomes. Although we cannot implement a complete DiD model–since proximity to the program is only meaningful after the program starts–we instead examine cross-sectional variation in financing rounds by estimating the following regression model:

$$Y_{it} = \beta_1 \text{BI\_Exposure}_i + \beta_3 X_i + \tau_t + \upsilon_{it}, \tag{4}$$

Where the outcome variable is either the log-transformed size or pre-money valuation of the investment. *BI_Exposure* is defines using one of three proxies (*Emplyee_Exposure*, *Patent_Exposure* or *State_Exposure*). X is a vector of fixed effects including, startup industry, state (excluded when using state exposure) or the sequence of number of VC Round and τ is a dummy for the year of the financing.

Our first exposure proxy indicates if the startup has hired a BI scientist. We identify BI scientists as co-authors on BI-funded academic papers and match these individuals against the employee rosters of *Neuro startups* using Revelio Labs data. For every financing round, we construct an indicator that equals one if the startup has hired at least one BI scientist up to that financing year (and zero otherwise), excluding startups that cannot be matched. Out of *495 Neuro startups* (with 1,446 financing events), 49 startups (accounting for 98 financing events) have hired at least one BI scientist. As reported in Table 5, these financing rounds were, on average, 100% larger in size (exp(0.696)) and achieved a 140% higher pre-money valuation.

To construct the next proxy, *Patent_Exposure*, we identify patents that were influenced by the BI, which is by the large language model discussed in Section 4. For every year, we count the number of startup's patents that are influenced by the BI up to that point and match this to the financing event in that year. As explained in Section 4 to avoid look ahead bias we only examine the influence of publications up to year (t) on patents applied for up to year (t+1) starting from 2015. This effectively reduces the number of rounds that can be included in this regression. Out of 826 financing rounds in this analysis the average round has 1.15 patents influenced by the BI. We then construct *Patent_Exposure* as log(1+number of influenced patents). The 25th percentile of rounds has zero patents influence by the BI and the 75th percentile has one patent. The coefficient of 0.249 in Column 2 of Table 5 thus indicates that moving from the 25th to the 75th percentile of the *Patent_Exposure* increases the round size increases by 18% (exp(0.2487×0.6931)-1. The effect on valuation however is not statistically significant.

The third proxy *State_Exposure* is the count of BI grants awarded to any instituituion in the startup's home state in a given year. The idea behind this measure is startups located in states where BI research has been active, are more likely to benefit from its spillovers. Similar to the previous measure, we log-transform the count of number of these grants in the state up to a given year and match it to the year of financing event. Neuro startups headquartered in states receiving more BI grants saw 57% larger rounds (coefficient=0.450, t=3.55) and 39% higher valuations (coefficient=0.330, t=2.13). Overall these

5.2.5. Robustness Tests

An alternative story for the more favorable VC financing could be because *Neuro startups* are operationally more established at the time VCs finance them. Under this scenario, the lower operational risk, a signal for quality, is the reason for larger round sizes, rather than R&D risk. We examine this possibility by checking the business status of the startup at the time of financing. We construct a dummy called *Generating Revenue*, which is equal to one if the startup has revenue at the round. Pitchbook designates the startup's business status as either "Generating Revenue" or "Profitable" at a given round. The other categories mostly include cases where a startup's business status is designated as "Startup", "Product Development", "Product in Beta Test" or "Clinical Trial".[40] We examine whether the startup is generating revenue at the round. The results are reported in the Appendix Table A12. Contrary to the story above, we find that *Neuro startups* are less likely to be generating revenue at the time of financing. This suggests that after the BI, VCs are more comfortable with funding *Neuro startups*, which are operationally less developed but perhaps have a lower R&D risk.

5.3. 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 6 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

[40] 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.

other healthcare sectors also grow, the more pronounced and immediate increase in *Neuro startup* acquisitions post-BI underscores the initiative's impact in making neurotechnology a standout area for investment, demonstrating that both venture capitalists and larger market players acknowledge the potential fostered by the BI's focus on neuroscience.

Nevertheless, an acquisition does not necessarily indicate a successful exit for the VC as acquisitions with a low premium could disguise failure (Puri and Zarutskie, 2012). Thus, to measure success more carefully, we follow the definition of *Successful Exit* outlined in 3. Besides, the *time to exit* is an alternative measure of VC investment success, calculated as the log of the number of days between the first VC investment and the exit date. For every startup, we run OLS regression of these variables following Equation 3, 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 6 reports the results of this specification. The $Neuro \times Post$ interaction term is central to the analysis, as it measures the differential impact of the BI on the probability of a successful exit for *Neuro startups*. We progressively limit the control firms from Columns (1) to (4), the positive and significant coefficients across the board from 0.087 in the healthcare sector to 0.128 in the overall sample, indicating that post-BI *Neuro startups* have a significantly higher probability of achieving successful exits compared to pre-BI, reinforcing the hypothesis that BI has enhanced the investability of *Neuro startups*. The coefficients signify that the odds of a successful exit increase by 8.7% to 12.8% for *Neuro startups* post-BI. This highlights the positive impact of the BI on these firms' exit outcomes. These results support the findings of increased VC investments in *Neuro startups* post-BI and extend the narrative to the broader market's recognition of these startups' value, as evidenced by their exit outcomes. The significant $Neuro \times Post$ coefficients across various specifications suggest that the BI's influence goes beyond attracting initial VC interest, translating into tangible, successful financial outcomes for *Neuro startups*.

Columns (5) to (8) of Table 6 analyze the impact on *time to exit*. The coefficients of the $Neuro \times Post$ interaction term are negative and statistically significant, indicating a reduction in exit time ranging from 11.6% for patenting startups to 25.6% for the overall sample. These findings suggest that *Neuro startups* have a shorter time to exit after the BI. This shorter exit time aligns more closely with the finite investment horizons of VC, thereby enhancing the attractiveness of *Neuro startups* to VC investors.

5.3.1. Aggregate Impact of the BI

We conduct two back-of-the-envelope calculations to gauge the BI's multiplier for VC investments. Since its announcement in 2013, the U.S. government has spent $4.837 billion on the BI. In the pre-BI period, 2000–2012, VCs invested $77.4 billion in healthcare startups. This grew to $269.7 billion between 2013 and 2022. Over the same period, VC investments in *Neuro startups* rose from $17.8 billion to $67.6 billion. Had neuro investments simply grown at the same pace as the broader healthcare sector, they would have reached $62.2 billion. The additional $5.3 billion appears attributable to the BI, implying a multiplier of approximately 1.1 based on total funds invested.

We conduct a similar analysis using exit outcomes, comparing the aggregate exit sizes of neuro and healthcare startups before versus after 2013. By this measure, *Neuro startups* gained an excess exit value of about $12.2 billion, translating into an estimated multiplier of around 2.5 federal dollars. These figures capture only the BI's impact on VC markets; they do not account for additional investments by strategic corporate players, angel investors, or other non-VC sources in the neuro space. Consequently, the overall economic impact of the BI is likely even greater than these estimates suggest.

5.4. Mechanisms

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

5.4.1. Academic Startups

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

In Table 7 we examine if post-BI *Neuro Startups* are more likely to be *Academic Startups*. Our focus here is capturing the engagement of academics with startups in the earliest stage of development, where uncertainty is high. Therefore, our *Post* variable is one if the founding year is 2013 or after, as opposed to the year of financing event. The results in Column (1) and (2) of Table 7 show that relative to all other VC-backed startups, post-BI *Neuro startups* are about 10% more likely to be an *Academic Startup*. However, despite the positive coefficient, in Columns (3) and (4), we do not find statistically significant results when we compare *Neuro Startups* to other healthcare or patenting startups. Figure 5, which plots the dynamic DiD estimates for the Column (3) specification, shows an upward trend in the likelihood of *Neuro Startups* becoming *Academic Startups* over time. A plausible explanation for the insignificant results driven by the earlier period could be that the effect of the BI for newly founded companies becomes more pronounced towards the end of the sample. This suggests that as BI produced more knowledge and advancements from this knowledge began to emerge, academics engaged more in *Neuro startups*.

5.4.2. Innovation and Academic Inventors

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

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

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

$$Y_{it} = \beta_1 Neuro_i \times Post_t + \beta_2 X_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{5}$$

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

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

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

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

5.4.3. Adaptability of Neuroscience

The BI promoted reallocation within neuroscience by opening new technological spaces integrating advances from other complementary fields. A decade after the program, NIH's BI director highlights several technologies emerging from the BI (Ngai, 2024). These include neural recording, neuromodulation therapies, brain-computer interfaces, neuro-inspired computer architectures, and precision circuit mapping. These advances reflect the Initiative's promotion of interdisciplinary projects as detailed in Section **??**. For example, AI, a key complementary technology, can help neuroscientists map complex brain activity that was previously intractable. At the same time, computer science has long drawn inspiration from neuroscience in advancing AI (e.g., neural networks). More modern examples are the development of energy-efficient neuromorphic AI architectures that are researching brain's remarkable computational power with little energy consumption. Similarly, the Initiative has funded consortia that developed standardized neural-interface protocols and translational platforms, harmonizing neural-signal acquisition with robotic control systems, Internet-of-Things connectivity and wearable device engineering. These integrated, closed-loop neurotechnology platforms support real-time decoding and feedback in applications ranging from implantable stimulators for movement disorders to adaptive, sensor-embedded wearables for cognitive monitoring. As such, we examine whether these BI-funded transformations in neuroscience spill over to sub-technologies within neurotech. We show that post-BI, neurotechnologies became more interdisciplinary and adaptable to other technologies, particularly AI and big data.

We define the complementary technology according to Pitchbook's technological vertical classifications, which are *Artificial Intelligence and Machine Learning, Big Data, Wearables & Quantified Self, Robotics, Internet of Things.* We estimate:

$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t + \beta_2 X_{it} + \tau_t + \upsilon_{ijt}, \tag{6}$$

where for startup i in year t, Y_{it} is an indicator variable equal to 1 if the startup has complementary technology in Pitchbook's technological vertical classifications. *Post* is an indicator variable equals to 1 if the startup was founded after 2013 and zero otherwise. The main coefficient of interest (β_1) is the interaction between *Neuro* and *Post*. λ_i and θ_t are firm and year-fixed effects.

Table 9 reports the estimation results from 6. Columns (1) and (2) compare *Neuro startups* with all other startups, with Column (2) restricting the sample to the 2008–2017 period. Columns (3) and (4) limit the comparison to startups within the healthcare sector, and Column (4) also uses the 2008–2017 sample period. As shown in Table 9, *Neuro startups* founded after 2013 are increasingly likely to operate in both neuroscience and complementary technologies, relative to similar control firms. All coefficients range from 0.051 to 0.094 and are statistically significant at the 10% level or better. For example, based on the 2008–2017 sample, the change in likelihood of *Neuro startups* to operate in interdisciplinary areas before and after the BI is 9.2% higher than relative changes for other startups in the healthcare industry.

Figure 7 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 6 shows the surge in the acquisition of *Neuro startups*. In Appendix Table A13, 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 A14 and A15, we repeat the exercise in Table 4, respectively. Our results are robust even if we exclude such startups.

6. Conclusion

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

While recent scrutiny has led to a temporary freeze on some of NSF and NIH funding, our findings underscore how these agencies fulfill a critical public-goods function. Their contribution is so foundational that it often goes unrecognized in downstream applications. In the case of neuroscience, for example, the BRAIN Initiative exemplifies how a targeted agenda can overcome coordination failures and mobilize follow-on private investment. More broadly, by financing early-stage discovery and experimentation, public agencies generate technological spillovers–new tools, data platforms, and conceptual breakthroughs–that underpin the longstanding dynamism and global leadership of the US venture capital and innovation.

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

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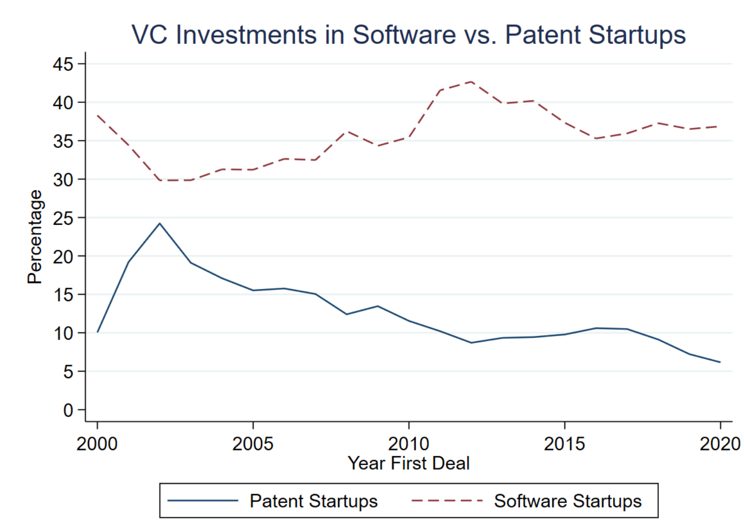


Figure 1. **VC Investments in Software vs. Patent-holding Startups**

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

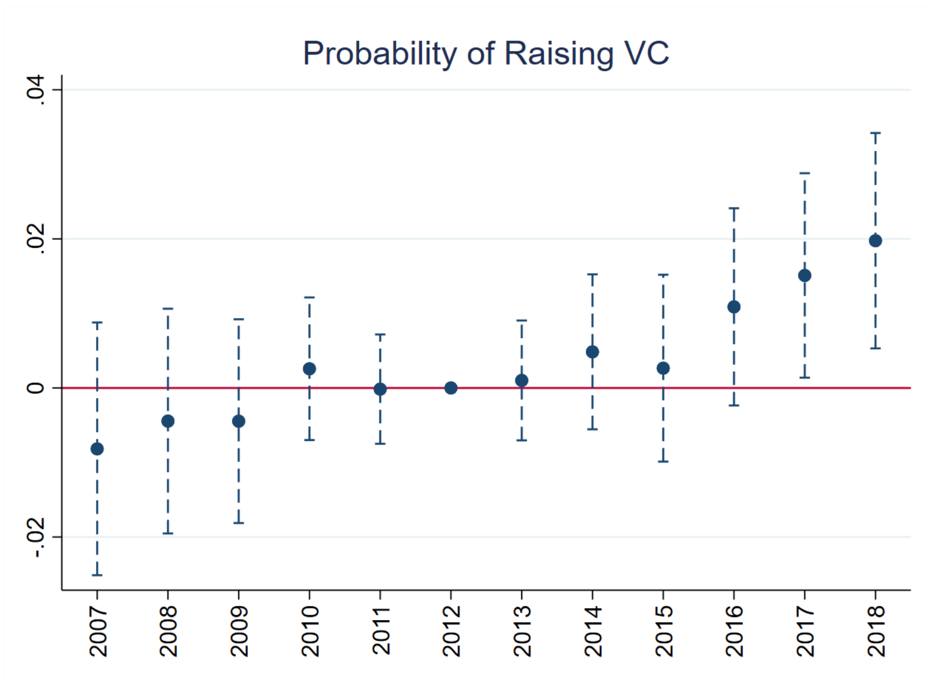


Figure 2. **Difference-in-difference estimates for Probability of Raising VC**

The figure plots the coefficients for the estimation of dynamic version of Equation 2, with interaction terms of each year and the *Neuro* dummy where the dependent variables are indicator variables for raising VC three years after being founded. The unit of observation is a startup-year. 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.

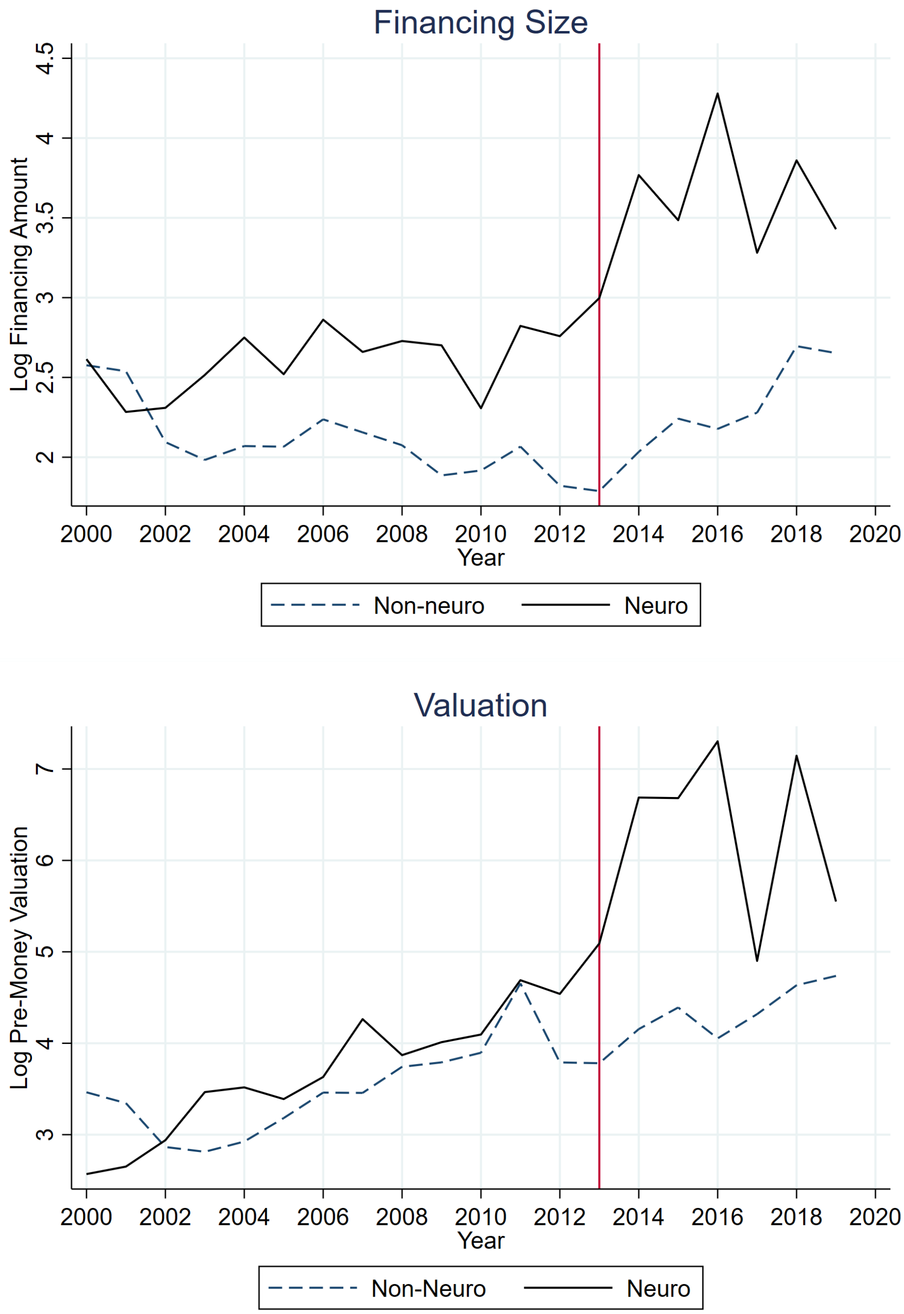


Figure 3. **Financing and Valuation of Neuro-Startups**

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.

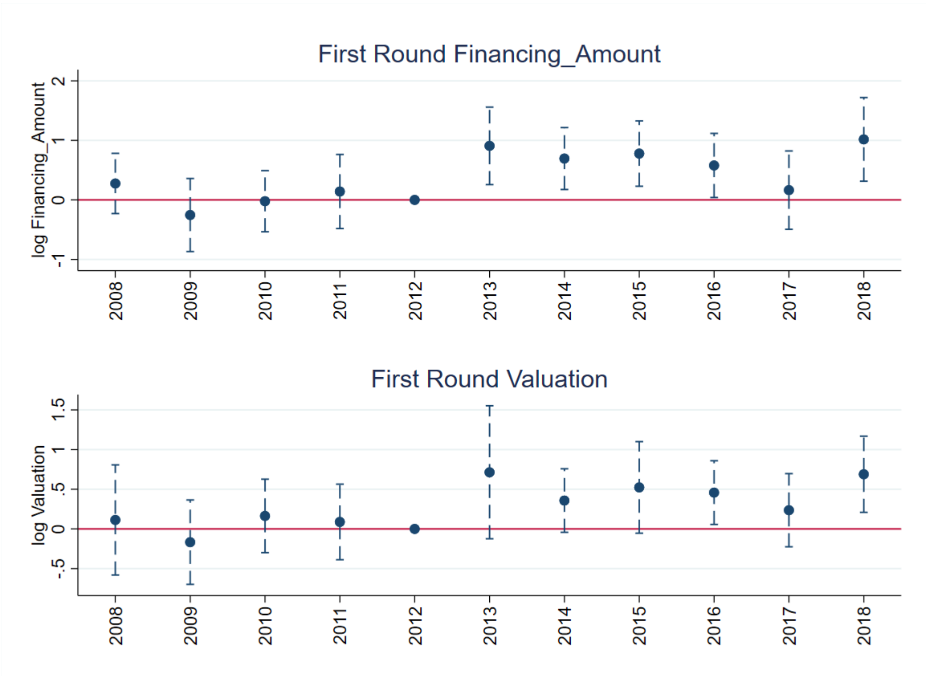


Figure 4. **Difference-in-difference estimates for financing and valuation: Neuro vs Other Healthcare**

The figure plots the coefficients for the estimation of dynamic version of Equation 3, with interaction terms of each financing year and the *Neuro* dummy where the dependent variables are the log of the financing amount and the log of the pre-money valuation. The figures only include the first rounds. The unit of observation is an entrepreneurial firm's first financing event. The 2012, i.e. t=(-1), interaction term is the excluded category, reported as zero in the figure. The vertical lines represent the 95% confidence interval for the coefficient estimates with robust standard errors.

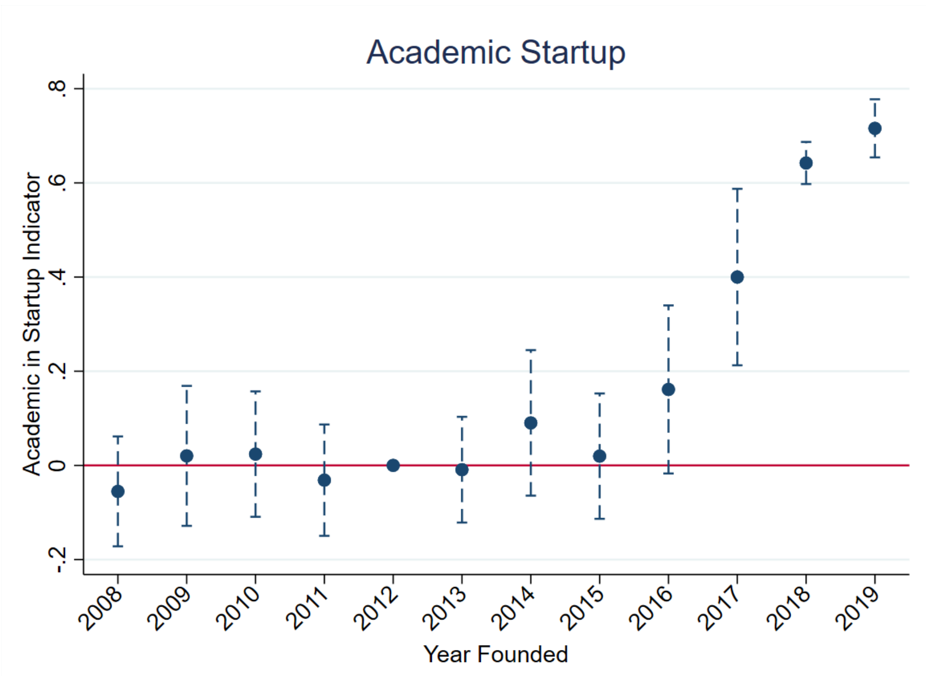


Figure 5. **Difference-in-difference estimates for Academic Startups: Neuro vs Other Healthcare**

The figure plots the coefficients for the estimation of dynamic version of Equation 3, 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.

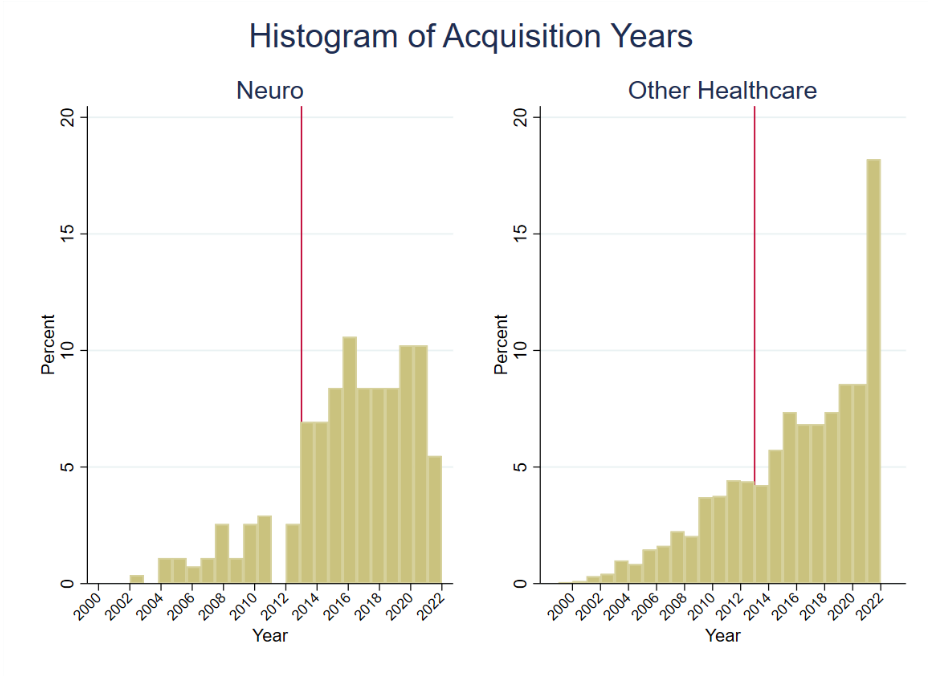


Figure 6. **Acquisitions of Neuro and other healthcare startups**

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

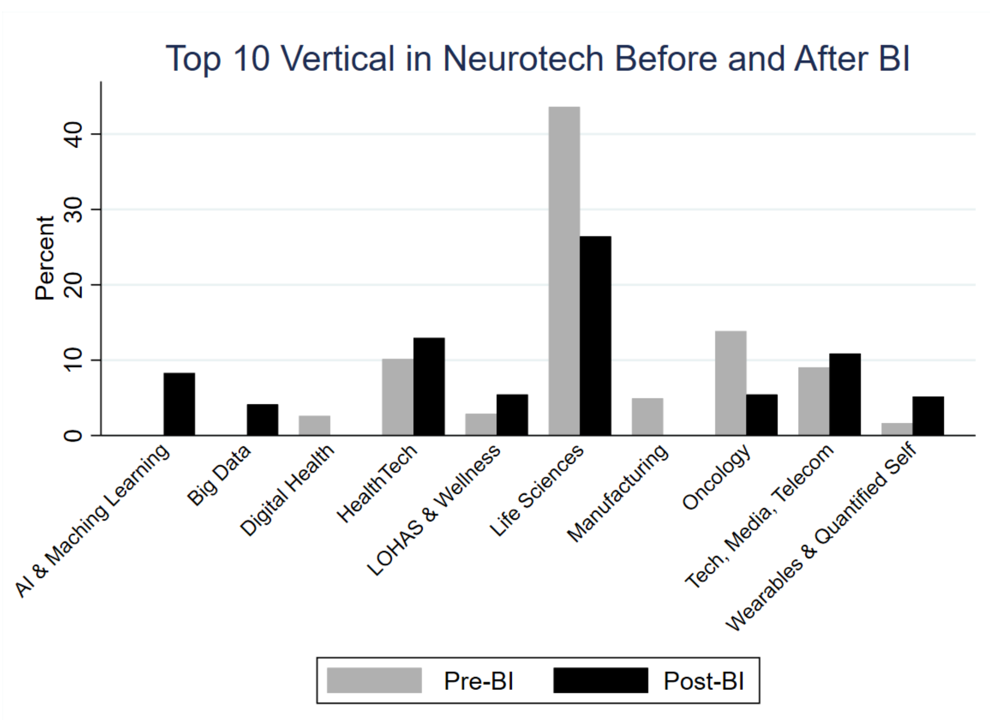


Figure 7. **Industry Verticals of Neuro Startups before and after the BI**

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=1	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	-	-	-	-	-
Employee_Exposure=1	1446	0.07	-	-	-	-
Patent_Exposure	826	1.15	4.37	0	0	2
State_Exposure	1634	100.33	108.56	1	47	283
Panel B: 1st Round						
Round Size	42,520	4.57	18.40	0.15	1.60	9.55
Pre-Money Valuation	19,661	12.78	125.71	1.62	6.00	20.00
Generating Revenue	42,515	0.43	0.49	0.00	0.00	1.00
Deal Year	42,520	2012.64	5.05	2005.00	2014.00	2018.00
#VCs	42,520	1.77	1.65	1.00	1.00	4.00
Panel C: Startup Level						
Successful Exit	29,003	0.12	0.33	0.00	0.00	1.00
Exit Year	29,003	2016.24	4.16	2011	2017	2021
#Patents	44,417	2.85	27.58	0.00	0.00	4.00
#Academic Founders	44,417	0.16	0.50	0.00	0.00	1.00
Neuro Startup	836	-	-	-	-	-
Panel D: Startups-Year Level for startups with at least one patents						
#Academic Inventors	104,069	0.22	1.69	0.00	0.00	0.00
#Patents	104,069	0.91	3.48	0.00	0.00	2.00

Table 2: **Valuation of Listed Firms' Neurotech & Similar Innovation Around the BI Announcement**. This table reports results from OLS regressions estimating Equation 1, where the dependent variable is the logged valuation of a patent, obtained from KPSS. A unit of observation is a listed firm's patent. *NeuroPat* is an indicator variable with a value of one for a neuro-related patent and zero for patents in similar technologies (as defined in Section 3.2. *Post* equals one for any grant date starting from April, 2, 2013, the announcement date of the BRAIN Initiative (2013) and zero otherwise. Columns (1-2) include patents granted between 2012 and 2013. Columns (3-4) and (5-6) drop the period between President Obama's State of the Union Speech on Feb 12, 2013, and the announcement date of the BI and cover symmetric windows of one and two years outside these windows, respectively. The t-statistics (in parentheses) are clustered at patent technology subclass ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

Panel A	OLS: Ln(Value of Patent)					
	2012–2013		[-1, +1] Year		[-2, +2] Year	
	(1)	(2)	(3)	(4)	(5)	(6)
NeuroPat × Post	0.122***	0.076**	0.151***	0.092***	0.314***	0.157***
	(3.29)	(2.31)	(4.69)	(2.85)	(8.29)	(5.35)
NeuroPat	-0.062***	-0.035*	-0.091***	-0.055**	-0.181***	-0.106***
	(-2.94)	(-1.87)	(-3.74)	(-2.53)	(-6.91)	(-5.90)
Post	-0.014*	-0.013*	-0.005	-0.007	-0.069***	-0.078***
	(-1.90)	(-1.75)	(-0.65)	(-0.96)	(-4.36)	(-4.78)
	80408	78435	80398	78444	166711	163986
Observations	0.962	0.962	0.999	0.998	0.994	0.995
Adj. R2	0.939	0.942	0.937	0.941	0.924	0.933
Firm FE	Y	N	Y	N	Y	N
Filing Year FE	Y	N	Y	N	Y	N
Firm X Filing Year FE	N	Y	N	Y	N	Y
Panel B	Poisson: # Citations					
	2012–2013		[-1, +1] Year		[-2, +2] Year	
	(1)	(2)	(3)	(4)	(5)	(6)
NeuroPat × Post	0.014	-0.011	0.073	0.076	0.053	0.036
	(0.19)	(-0.12)	(1.10)	(0.86)	(0.77)	(0.38)
NeuroPat	-0.692***	-0.745***	-0.745***	-0.816***	-0.769***	-0.818***
	(-2.74)	(-2.81)	(-3.24)	(-3.37)	(-2.83)	(-2.87)
Post	-0.255***	-0.234***	-0.270***	-0.248***	-0.364***	-0.357***
	(-5.58)	(-4.83)	(-7.13)	(-6.15)	(-7.83)	(-6.92)
Observations	80371	78243	80361	78253	166669	163688
Adj. R2	0.939	0.942	0.937	0.941	0.924	0.933
Firm FE	Y	N	Y	N	Y	N
Filing Year FE	Y	N	Y	N	Y	N
Firm X Filing Year FE	N	Y	N	Y	N	Y

Table 3: **Probability of Raising Venture Capital**. This table reports results from OLS panel regressions estimating Equation 2, where the dependent variable is an indicator variable equal to one if the firm has raised venture capital and zero otherwise. The analysis is at the firm-year level. *Neuro* is an indicator variable with a value of one for a *Neuro startup* and zero for other similar patenting startups in the similar technology space, as described in Section 3.3.1. *Post* equals one for years in the 2013-2019 period. Columns 1 and 2 include data from the entire sample period, and Columns 3 and 4 include a five-year window before and after the BI. The *t*-statistics (in parentheses) are clustered at the startup level. ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

	Received_VC			
	All Years		2007-2018	
	(1)	(2)	(3)	(4)
Neuro×Post	0.023***	0.022***	0.015***	0.015**
	(3.44)	(3.34)	(2.60)	(2.55)
Ln(Firm Age)		0.062***		0.067***
		(34.50)		(31.77)
Observations	290989	290989	222941	222941
Adj R-squared	0.718	0.723	0.771	0.776
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 4: Funding Size and Valuation. This table presents the results of OLS regressions estimating Equation 3. The dependent variable is the log of investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is a VC financing event of an entrepreneurial firm. The variable *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the announcement of the BRAIN Initiative (2013). *# Investors* counts the number of investors in the round. Fixed effects for both panels are presented at the bottom of the table and include dummies for the year of financing event, Pitchbook's 41 industry groups and the state of the startup's headquarters. Tables A9, A10, and A11 provide results for the sample including all financing rounds and explore alternative classifications of *Neuro* as robustness checks. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Columns (1-2) and are clustered at the firm level in Columns (3-4). ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(Investment Size)**			
	First Round		All Rounds	
	All	Healthcare	All	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.494***	0.392***	0.278***	0.213***
	(5.05)	(3.55)	(4.16)	(3.13)
Neuro	0.083	0.128*	0.111**	0.123**
	(1.32)	(1.89)	(2.18)	(2.34)
Ln(# Investors)	0.376***	0.488***	0.645***	0.759***
	(48.18)	(23.70)	(106.24)	(58.01)
Observations	39550	7989	106416	23701
Mean Outcome	0.579	0.857	1.285	1.491
Adj R-squared	0.168	0.180	0.363	0.361
Panel B:	**Ln(Valuation)**			
	First Round		All Rounds	
	All	Healthcare	All	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.363***	0.416***	0.237***	0.235***
	(3.53)	(3.51)	(2.69)	(2.71)
Neuro	-0.007	-0.033	0.138**	0.058
	(-0.11)	(-0.44)	(2.16)	(0.87)
Ln(# Investors)	0.213***	0.225***	0.374***	0.316***
	(22.77)	(10.26)	(47.36)	(20.70)
Observations	19587	4202	60670	13590
Mean Outcome	1.778	1.863	2.917	2.957
Adj R-squared	0.080	0.089	0.490	0.457
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round # FE	N	N	Y	Y

Table 5: Exposure to the BRAIN Initiative and Funding Variation within Neuro startups. This table presents the results of estimating Equation 4, which examines the relation between BI exposure proxies and the characteristics of *Neuro Startups'* financing rounds post-2013. The unit of observation is a VC financing event. The dependent variable is the log of VC investment amount in Columns (1-3) and the log of pre-money valuation in Columns (4-6). *Employee_Exposure* is an indicator variable equal to one for whether the firm has hired at least one BI scientist up to the financing year and zero otherwise. *Patent_Exposure* is the number of patents influenced by the BI up to the financing year, as identified by the large language model (Section 4). *State_Exposure* is the number of BI grants awarded to the institutions in the startup's state. *# Investors* counts the number of investors in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round #* are dummies for the sequence number of VC financing rounds. The t-statistics (in parentheses) are based on standard errors clustered at the startup level , with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

	Ln(Investment Size)			Ln(Valuation)		
	(1)	(2)	(3)	(4)	(5)	(6)
Employee_Exposure	0.696***			0.868***		
	(3.03)			(3.38)		
Ln(Patent_Exposure+1)		0.249**			0.082	
		(2.47)			(0.88)	
Ln(State_Exposure+1)			0.254***			0.174***
			(4.89)			(2.81)
Ln(# Investors)	0.758***	0.804***	0.794***	0.343***	0.422***	0.355***
	(17.58)	(15.06)	(19.23)	(7.02)	(6.50)	(7.80)
Observations	1446	826	1634	1006	565	1109
Mean Outcome	2.358	2.412	2.295	3.909	4.030	3.878
Adj. R2	0.449	0.477	0.390	0.559	0.554	0.499
Industry FE	Y	Y	Y	Y	Y	Y
VC Round # FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	N	Y	Y	N

Table 6: Success of the Exits. This table reports results from OLS regressions estimating Equation 3, where the dependent variable is an indicator variable for successful exits. A unit of observation is an entrepreneurial firm. *Successful Exit* is defined as an IPO or a M&A at a reported value at least twice the total capital invested. *(Time to Exit)* is the difference between the number of days between the first VC investment and the VC exit date. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for startups receiving the first VC financing event after the BRAIN Initiative (2013), where the year of the event itself has been excluded. *First VC Financing Year FE* (*Exit Year*) indicate dummies for financing (exit) year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

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

Table 7: Academic Startup. This table reports results from OLS regressions estimating Equation 3, where the dependent variable is an indicator variable for whether the startup uses *Academic Startup*. *Academic Startup* are startups with at least one academic holding a senior position within the startup; see Section 3.5.1 for more details. A unit of observation is an entrepreneurial firm. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for startups receiving the first VC financing event after the BRAIN Initiative (2013), where the year of the event itself has been excluded. *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *Founding Year FE* indicate dummies for founding year. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

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

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

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

Table 9: Integration with Complementary Technologies. This table reports results from OLS regressions estimating Equation 3, where the dependent variable is an indicator variable for whether the startup uses at least one *Complementary technology* according to Pitchbook's technological vertical classifications. These technologies includes: *Artificial Intelliegence and Machine Learning, Big Data, Wearables & Quantified Self, Robotics, Internet of Things*. See Section 5.4.3 for more details. A unit of observation is an entrepreneurial firm. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for startups being founded after the BRAIN Initiative's announcement year (2013). *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *Founding Year FE* indicate dummies for the year company was fonded. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

	Complementary Technologies			
	All		Healthcare	
		[08-17]		[08-17]
	(1)	(2)	(3)	(4)
Neuro × Post	0.068**	0.094***	0.051*	0.092***
	(2.21)	(2.77)	(1.65)	(2.76)
Neuro	0.040***	0.015	0.003	-0.032**
	(4.14)	(0.81)	(0.41)	(-2.18)
Observations	48539	32340	9337	5817
Mean outcome	0.145	0.172	0.101	0.130
Adj. R2	0.109	0.107	0.100	0.096
Industry FE	Y	Y	Y	Y
Founding Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y

Appendix A: BRAIN Initiative Funding and Grants

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

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

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

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

A.2. NIH vs NSF

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

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

Appendix B: Name-matching

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

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

Appendix C: Analyzing the commercial and scientific impact of BI

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

We further test the difference in the number of citations for BI patents via a regression model in the Panel A of Table A3. Because most publications never receive a patent citation, we use a Poisson model to accommodate for an outcome variable with many zero values (Cohn et al., 2022). In Column (1), we regress the number of citations on a dummy variable for BI patents and include year fixed effects to capture time trends in citations. In Column (2), we repeat this exercise for a sub-sample of non-BI NIH-backed neuroscience papers. Across both specifications, we find a positive coefficient indicating the higher citations received by BI publications. Masclans et al. (2024) argue that patent citations reflect the ex post commercialization of an academic article but not its ex ante potential. They, therefore, develop a large language model (LLM) trained on a dataset of renewed patents— such patents are presumably more commercialized. This trained model is then used to generate two scores for each publications: commercial and scientific potential. We link these scores to the academic articles in our sample. In Column 3, we add the commercial and scientific potential scores as control variables. The coefficient on BI is still statistically significant, and indicates that BI publications are four times more likely to receive a citation from a patent compare to non-BI neuroscience. In Panel B, we directly compare the summary statistics on these scores across BI and non-BI neuroscience publications. The average commercial potential of non-BI grants after 2014 is 0.69, which is smaller than the commercial potential of BI publications at 0.78. The difference between the commercial potential of BI grants and non-BI grants is statistically significant at the 99% level, suggesting that research under BI grants is more commercializable than similar research grants in the sample period. .[41]

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

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

Appendix D: Cross-Sectional Analysis on Probability of Raising Venture Capital

Section 5.1 shows that the BI expands the extensive margin using a panel regression. However, a concern with panel regressions is that older firms naturally accumulate more observations, leading to the over-representation of older startups. To address this, we restrict the sample to early-stage startups and estimate a cross-sectional DiD model on the likelihood of raising VC. The results are directionally and statistically similar to the panel structure. The cross-sectional DiD model we estimate is as follows:

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

$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t + \beta_2 \text{Neuro}_i + \lambda_t + \gamma_t + \rho_t + \upsilon_{ipt} \tag{7}$$

where Y_{ipt} equals one if the startup raises VC and 0, otherwise. Neuro_i is an indicator for whether the startup is a *Neuro startup* as defined in Section 3.3. Post_t equals one if the startup files for its first patents after 2013 and zero, otherwise. Our results are robust if we define *Post* based on the founding year. The advantage of first patenting year is that it represents when the company is innovation-active, with more tangible IP and, therefore, a legitimate candidate for raising VC. The key coefficient of interest is (β_1), which is the interaction between *Neuro* and *Post*. λ_i, γ_i, and ρ_t represent the founding and the first patenting year fixed effects, respectively. They control for the temporal dynamics of innovation and funding. To ensure that we study the probability of receiving VC as a result of the firm's technology and not the other way around, in this analysis, we exclude companies that file their first neuro or similar patent after receiving VC.

Table A5 presents the results of the OLS regression of Equation 7. Column (1) includes observations from the entire sample period, while Column (2) focuses on the sample from 2008 to 2017 for a time-balanced sample around the shock. The coefficients of the interaction term (β_1) in both columns are positive and statistically significant, suggesting that following the BI, *Neuro startups* are more likely to receive VC financing than other similar startups founded and filing their first patents in the same year.

For a closer mapping between the timing of the BI, startup innovation and receiving VC, in Columns (3-5), we restrict our sample to startups that filed their first neuro patent (i.e., treated group) or similar patent (i.e., control group) within three years of being founded. $beta_1$ in Columns 3, and the time-balanced Column (4), is positive and statistically significant. This suggests that among younger firms, *Neuro startups* are more likely to receive VC financing than similar startups post-BI. These results are likely underestimated because our three-year window means that BI partially affects startups founded between 2010 and 2012. For example, a *Neuro startup* that was founded in 2012 and filed for its first *Neuro patent* in the same year is partially treated in 2012. To minimize bias, in Column (5) we exclude startups founded between 2010 and 2012. In line with the underestimation, $beta_1$ in Column (5) becomes larger in magnitude and statistical significance. These results suggest that the BI has caused VCs to lower their investment hurdle in neuro space, in line with crowding in.

We also estimate the dynamic version of Column (4) of Table A5, replacing *Post* with year dummies. The figure does not suggest the existence of a pre-trend in the probability of raising VC for the treated group. It shows that the likelihood of *Neuro startups* securing VC funding increases only after the BI announcement. The coefficient for the year 2011 is above zero. Similar to the explanation above, note that the outcome variable here measures whether the startup has raised VC in the next three years. Thus, it is likely that some of the startups founded in 2011 have benefited from the more favorable VC environment induced by the BI.

Appendix Figures and Tables

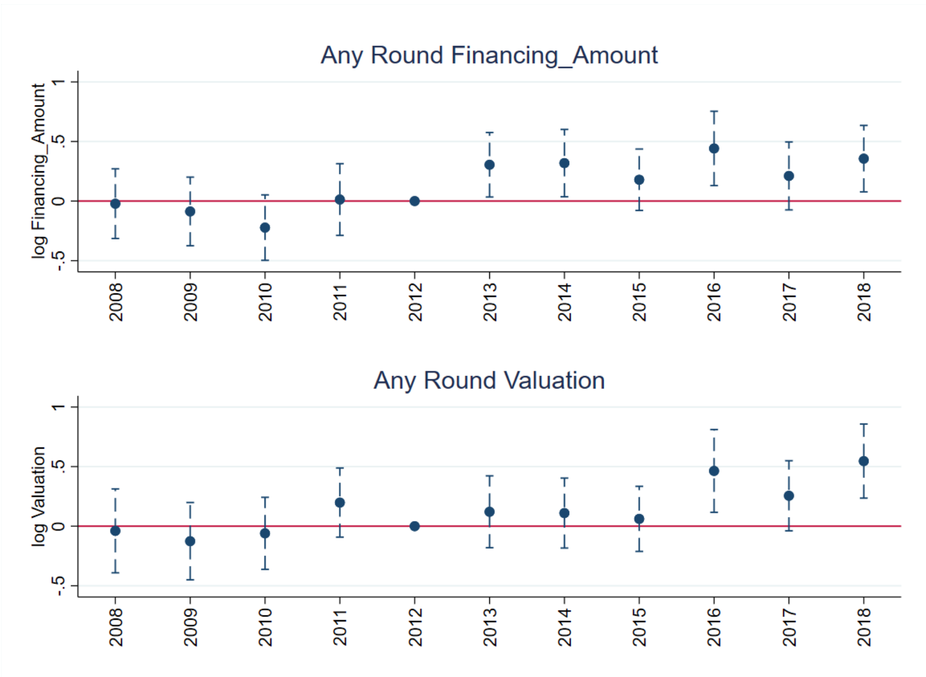


Figure A.1. **Difference-in-difference estimates for financing and valuation: Neuro vs Other Healthcare**

The figure plots the coefficients for the estimation of dynamic version of Equation 3, with interaction terms of each financing year and the *Neuro* dummy where the dependent variables are the log of the financing amount and the log of the pre-money valuation. These two figures include all rounds. The unit of observation is an entrepreneurial firm's first financing event. The 2012, i.e. t=(-1), interaction term is the excluded category, reported as zero in the figure. The vertical lines represent the 95% confidence interval for the coefficient estimates with robust standard errors.

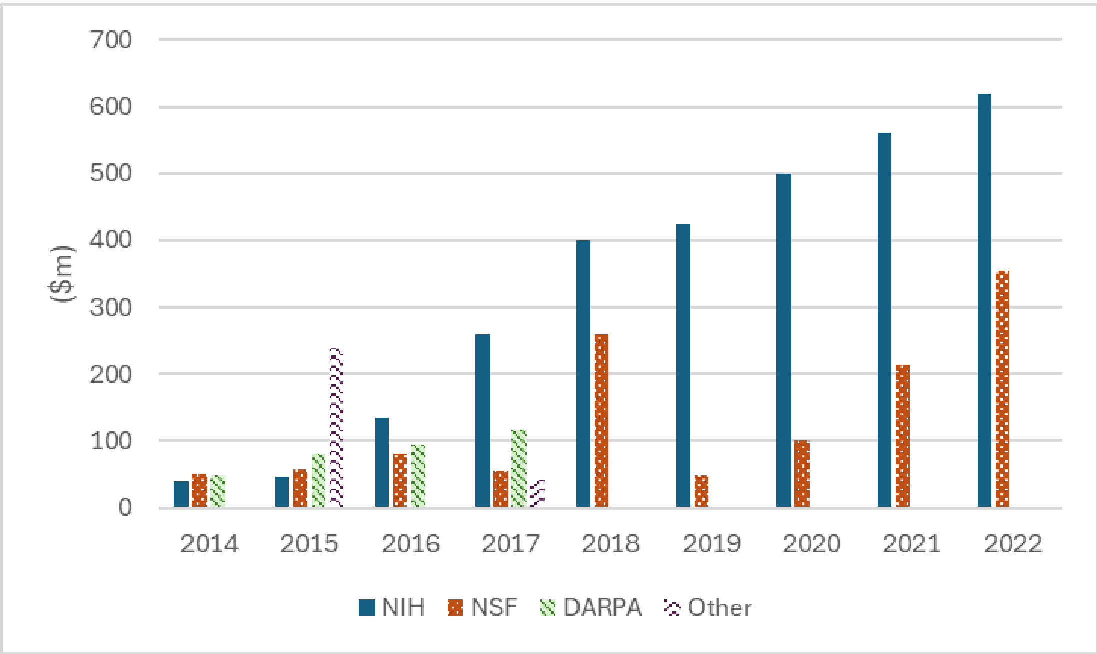
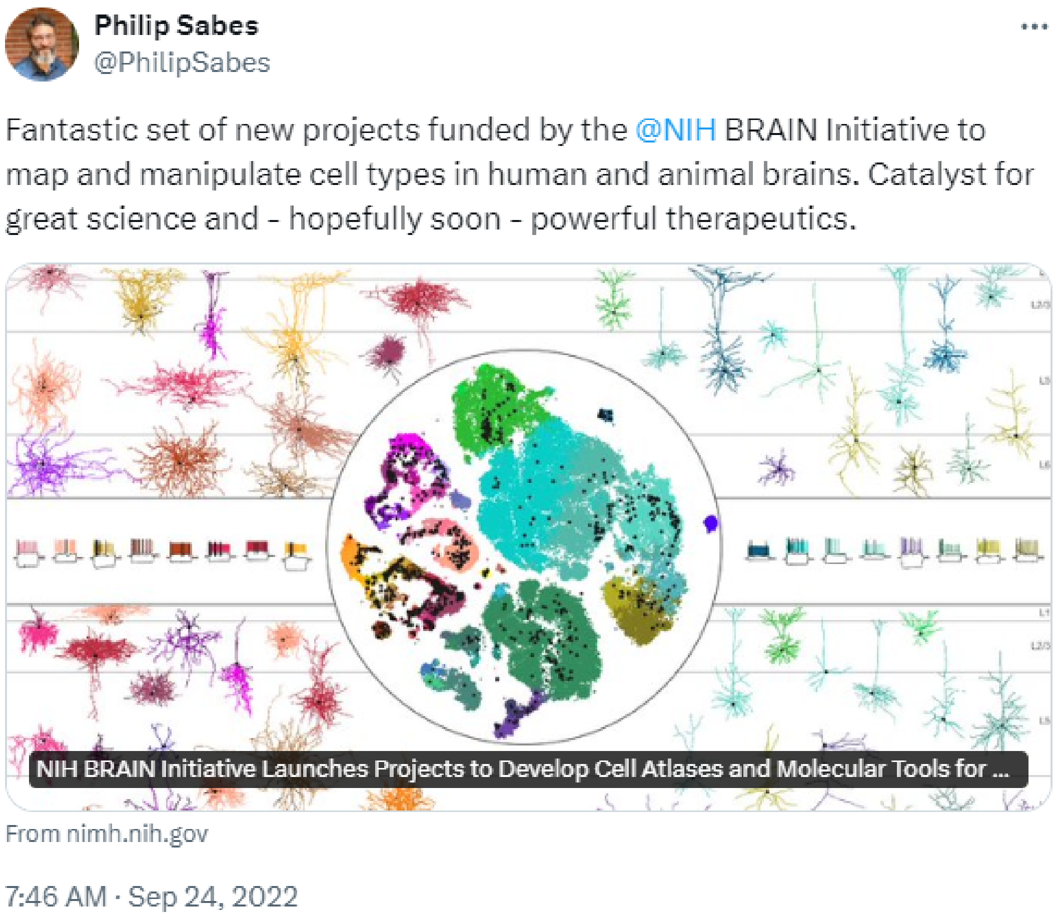


Figure A.2. **Total BRAIN Initiative Funding per Agency**

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



Philip Sabes
@PhilipSabes

Fantastic set of new projects funded by the @NIH BRAIN Initiative to map and manipulate cell types in human and animal brains. Catalyst for great science and - hopefully soon - powerful therapeutics.

NIH BRAIN Initiative Launches Projects to Develop Cell Atlases and Molecular Tools for ...

From nimh.nih.gov

7:46 AM · Sep 24, 2022

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

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

Table A1: Variables Definitions

Variable name	Definitions	Tables
Independent variables		
Neuro	The indicator variable equals one if the startup is a *Nuero Startup*; zero otherwise. *Neuro Startup* is identified as startups granted at least one patent within neuroscience-related technology groups, as detailed in Section 3.3.	Table 4, 6, 7, 8,A12, A14,A15
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 4, 6,7, 8,A12, A14,A15
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 **??**
Ln (# VCs)	The natural logarithm of the number of VCs in the round. Sources: PitchBook	Table 4, **??**,A12,A14,A15
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 6
Ln(Total $ Raised)	The natural logarithm of the total amount of financing that the startup has raised up to the year. Sources: PitchBook	Table 8
Dependent Variables		
Ln(round size$)	The natural logarithm of VC financing amount, excluding below $0.1m financing amounts. Sources: PitchBook	Table 4,**??**, A14
Ln(Pre-Money Valuation$)	The natural logarithm of VC Pre-Money Valuation, excluding below $0.1m valuations. Sources: PitchBook	Table **??**,A15
Successful Exit	The indicator variable equals one for startups' successful exit. A successful exit is an IPO or an M&A at a reported value at least twice the total capital invested. Sources: PitchBook	Table 6
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 7
#Patents	Startup i's the total number of patents filed (and eventually granted) in year t	Table 8
#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 8
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 8
#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 8
Generating Revenue Dummy	The indicator variable equals one for startup is generating revenue; zero otherwise.	Table A12

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

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

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

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

Panel B: Predicted Commercial Potential of Publications			
	BI (A)	Non-BI Neuroscience post 2014 (B)	(A-B)
Mean	0.78	0.69	0.09***
Median	0.84	0.78	0.06***
SD	0.17	0.26	

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

2015

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

2016

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

2017

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

2018

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

2019

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

2020

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

Table A5: **Probability of Raising Venture Capital**. This table reports results from OLS regressions estimating Equation 7, where the dependent variable is the indicator variable for VC financing, which equals one if the startup receives VC financing and zero. The unit of observation is a firm. *Neuro* is an indicator variable with a value of one for a *Neuro startup* and zero for other similar patenting startups in the similar technology space, as described in Section 3.3.1. *Post* equals one if the startup's first patent filing year is after 2013 and 0, otherwise. The sample includes only startups that file their first patent before receiving their first VC financing. Column 1 includes data from the entire sample period. Column 2 includes startups that were founded between 2008 and 2017. Columns (3-5) include startups that filed their first patents within three years of being founded. The dependent variables in Columns (3-5) are indicator variables that equal one if the startup receives its first VC financing within three years after founding. Column 5 excludes startups that were founded between 2010 and 2012 and include five years before and after this period. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors. ***, ** and * representing significance at the 1%, 5% and 10% levels, respectively.

	Received VC		Received VC in 3Y after being founded		
		[08-2017]		[08-17]	[05-09] & [13-17]
	(1)	(2)	(3)	(4)	(5)
Neuro × Post	0.047*	0.080**	0.076**	0.090**	0.139***
	(1.91)	(2.06)	(2.42)	(2.06)	(3.68)
Neuro	0.029*	0.010	0.025	0.018	-0.026
	(1.86)	(0.33)	(1.31)	(0.53)	(-1.10)
Observations	19395	9933	12554	7329	6886
Adj. R2	0.053	0.052	0.048	0.044	0.050
Mean outcome	0.121	0.148	0.108	0.131	0.124
Firm FE	Y	Y	Y	Y	Y
Founding Year FE	Y	Y	Y	Y	Y
1st Patenting Year FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y

Table A6: Pre-treatment trend This table repeats Equation 3 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 3 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 A7: Funding Size and Valuation (Balanced Window Around the Shock). This table presents the results of OLS regressions estimating Equation 3. The dependent variable is the log of investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is a VC financing event of an entrepreneurial firm. The variable *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the announcement of the BRAIN Initiative (2013). The sample is restricted to financing rounds five year before and after the announcement of the BI (2008-2017). *# Investors* counts the number of investors in the round. Fixed effects for both panels are presented at the bottom of the table and include dummies for the year of financing event, Pitchbook's 41 industry groups and the state of the startup's headquarters. Tables A9, A10, and A11 provide results for the sample including all financing rounds and explore alternative classifications of *Neuro* as robustness checks. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Columns (1-2) and are clustered at the firm level in Columns (3-4). ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(Investment Size)**			
	First Round		All Rounds	
	All	Healthcare	All	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.306**	0.311**	0.279***	0.220***
	(2.47)	(2.23)	(3.64)	(2.88)
Neuro	0.257***	0.231**	0.198***	0.178***
	(2.79)	(2.28)	(3.16)	(2.73)
Ln(# Investors)	0.297***	0.406***	0.526***	0.659***
	(32.03)	(15.29)	(69.23)	(38.27)
Observations	25148	4866	58211	12549
Mean Outcome	0.389	0.727	1.001	1.254
Adj R-squared	0.114	0.158	0.310	0.318
Panel B:	**Ln(Valuation)**			
	First Round		All Rounds	
	All	Healthcare	All	Healthcare
	(1)	(2)	(3)	(4)
Neuro×Post	0.349***	0.431***	0.208**	0.198**
	(2.70)	(2.85)	(2.14)	(2.24)
Neuro	0.018	-0.036	0.235***	0.131*
	(0.18)	(-0.33)	(2.98)	(1.69)
Ln(# Investors)	0.186***	0.203***	0.304***	0.241***
	(16.67)	(7.25)	(30.57)	(11.92)
Observations	12258	2501	32780	7112
Mean Outcome	1.693	1.777	2.644	2.718
Adj R-squared	0.066	0.092	0.434	0.426
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round # FE	N	N	Y	Y

Table A8: Funding Size and Valuation. This table presents the results of OLS regressions estimating Equation 3. The dependent variable is the log of investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is a VC financing event of an entrepreneurial firm. The variable *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the announcement of the BRAIN Initiative (2013). *# Investors* counts the number of investors in the round. Fixed effects for both panels are presented at the bottom of the table and include dummies for the year of financing event, Pitchbook's 41 industry groups and the state of the startup's headquarters. Tables A9, A10, and A11 provide results for the sample including all financing rounds and explore alternative classifications of *Neuro* as robustness checks. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Columns (1-2) and are clustered at the firm level in Columns (3-4). ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(Investment Size)**					
	First Round			All Rounds		
	Cancer	Patent	SimilarTech	Cancer	Patent	SimilarTech
	(1)	(2)	(3)	(4)	(5)	(6)
Neuro×Post	0.482**	0.321***	0.268**	0.149	0.145**	0.100
	(2.04)	(3.18)	(2.53)	(1.13)	(2.19)	(1.47)
Neuro	-0.061	0.026	0.037	0.064	0.108**	0.129**
	(-0.32)	(0.39)	(0.53)	(0.58)	(2.11)	(2.40)
Ln(# Investors)	0.452***	0.432***	0.448***	0.715***	0.746***	0.756***
	(5.51)	(24.15)	(21.09)	(16.83)	(66.63)	(58.70)
Observations	578	8561	6210	1855	31154	23461
Mean Outcome	0.943	0.938	0.995	1.631	1.724	1.810
Adj R-squared	0.161	0.161	0.164	0.352	0.382	0.391
Panel B:	**Ln(Valuation)**					
	First Round			All Rounds		
	Cancer	Patent	SimilarTech	Cancer	Patent	SimilarTech
	(1)	(2)	(3)	(4)	(5)	(6)
Neuro×Post	0.466**	0.234**	0.230**	0.214	0.106	0.077
	(2.12)	(2.17)	(2.03)	(1.42)	(1.20)	(0.85)
Neuro	-0.069	0.019	0.000	0.017	0.196***	0.215***
	(-0.41)	(0.27)	(0.00)	(0.13)	(3.05)	(3.20)
Ln(# Investors)	0.258***	0.192***	0.208***	0.255***	0.411***	0.408***
	(2.96)	(9.77)	(8.88)	(5.04)	(28.07)	(24.80)
Observations	336	5125	3823	1177	20188	15547
Mean Outcome	1.813	1.938	1.964	3.062	3.264	3.336
Adj R-squared	0.088	0.076	0.085	0.523	0.496	0.503
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
VC Round # FE	N	N	N	Y	Y	Y

Table A9: Funding Size. This table presents the results of OLS regressions estimating Equation 3. The dependent variable is the log of VC investment amount in Panel A and the log of pre-money valuation in Panel B. A unit of observation is an entrepreneurial firm VC financing event. *Neuro* is a dummy variable for startups with at least one patent with a neuroscience keyword. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. *VC Round FE* are dummies for the sequence of financing rounds. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

Panel A:	**Ln(Round Size $ for All Rounds)**			
	All	Healthcare		Patenting
			[08-17]	
	(1)	(2)	(3)	(4)
Neuro×Post	0.287***	0.221***	0.225***	0.147**
	(4.29)	(3.28)	(2.97)	(2.22)
Neuro	0.101**	0.113**	0.168***	0.107**
	(1.97)	(2.15)	(2.61)	(2.09)
Ln(# Investors)	0.613***	0.763***	0.683***	0.711***
	(107.18)	(60.01)	(39.69)	(67.16)
Observations	106576	23737	12567	31194
Mean Outcome	1.285	1.491	1.255	1.725
Adj R-squared	0.365	0.371	0.330	0.384
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y

Panel B:	**Ln(Pre-Money Valuation $ for All Rounds)**			
	All	Healthcare		Patenting
			[08-17]	
	(5)	(6)	(7)	(8)
Neuro×Post	0.241***	0.239***	0.202**	0.106
	(2.74)	(2.76)	(2.29)	(1.21)
Neuro	0.132**	0.052	0.126	0.193***
	(2.06)	(0.79)	(1.62)	(3.00)
Ln(# Investors)	0.340***	0.306***	0.235***	0.382***
	(46.81)	(21.10)	(12.14)	(28.11)
Observations	60739	13612	7126	20218
Mean Outcome	2.918	2.957	2.718	3.265
Adj R-squared	0.491	0.462	0.432	0.500
Industry FE	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
VC Round FE	Y	Y	Y	Y

Table A10: Funding Size. This table presents the results of OLS regressions estimating Equation 3. The dependent variable is the log of VC investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is the first VC financing event of an entrepreneurial firm, and only the first rounds are included in this table. The variable *Neuro (Def 2)* is a dummy variable for a neurotech startup; a neurotech startup is a firm that files for a neuro patent within the first five years after its founding. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

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

Table A11: Funding Size. This table presents the results of OLS regressions estimating Equation 3. The dependent variable is the log of VC investment amount in Panel A and the log of pre-money valuation in Panel B. The unit of observation is the first VC financing event of an entrepreneurial firm, and only the first rounds are included in this table. The variable *Neuro (Def 3)* is a dummy variable for a neurotech startup; the neurotech startup is defined as a startup's business description contains one of our *Neuro keywords*: {*neuro, nerve, brain, optogenetic, Parkinson, Alzheimer, and dementia*}. *Post* equals one for any year after the BRAIN Initiative (2013), where the year of event itself has been excluded. *# VCs* counts the number of VCs in the round. *Year FE* indicate dummies for financing year, *Industry FE* are dummies for Pitchbook's 41 industry groups. *State FE* are dummies for entrepreneurial firm headquarters state. The t-statistics (in parentheses) are based on heteroskedasticity-robust standard errors in Panel A, and clustered at the startup level in Panel B, with ***, ** and * representing significance at the 1%, 5%, and 10% levels, respectively.

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

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

Table A12: Startups' Revenue Status. This table reports results from OLS regressions estimating Equation 3, 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 A13: 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 A14: Funding Size without AI and Big Data Startups. This table repeats the exercise in Table 4, 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 A15: Valuations without AI and Big Data Startups. This table repeats the exercise in Table 4, 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