

Venture Capital Response to Government-Funded Basic Science

Roham Rezaei & Yufeng Yao

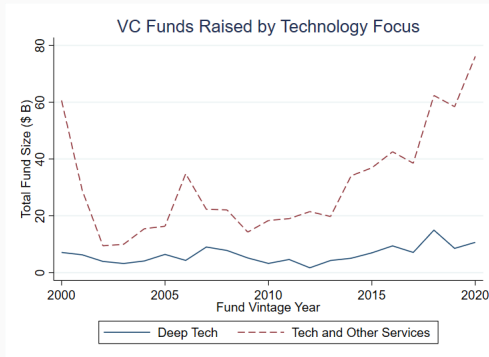
May 19, 2025

UNSW
ABFER 2025

Private markets and funding science-based innovation

- To address societal challenges (e.g., climate change and Alzheimer's disease) we need to invest in new technologies
 - Private markets may underinvest in basic science (Nelson, 1959; Arrow, 1962)
 - High technical uncertainty & difficulty in appropriation due to large externalities
 - Social value of basic science R&D > Private value
- The government should bridge the funding gap in basic science.
- The knowledge and human capital are supplied as a **public good** to the market to commercialize.

VC as a market mechanism for financing innovation



VC model is not conducive to reducing uncertainty in basic science
(Kerr, Nanda, Rhodes-Kropf, 2014; Lerner and Nanda, 2020)

- Long R&D timelines and finite life VC funds
- Staged financing not amenable to costly initial experimentation
- Large-scale investments required beyond the scale of VC funds

Does an expected reduction in technical uncertainty, **as a result of a government intervention**, crowds in VC investments? Channels?

Government-funded basic science and VCs

- Does an expected reduction in technical uncertainty, **as a result of a government intervention**, crowds in VC investments?
Channels?



NIH cuts billions of dollars in biomedical funding, effective immediately

Researchers say it would hurt facilities that work on medical issues such as cancer research and heart disease. Elon Musk contends the old policy was “a ripoff.”



Government-funded basic science and VCs

- Many publicly funded research projects do not generate a significant market response
 - Fusion energy, cosmology, particle physics
- The design of government funding could be inefficient
 - SBIR Phase II grants (Howell, 2017)
- Large public programs may even crowd out VCs
 - e.g., by competing over talent and resources
- **Mission-oriented government R&D programs**
 - Nuclear energy, antibiotics, mRNA vaccines
 - Also for the IT sector: GPS, radar, internet, Google search algorithms, web browsers, Cisco's routers

Brain Research Through Advancing Innovative Neurotechnologies (BRAIN)

- Identified in 2013 by Obama as a *Grand Challenge*
 - A large-scale mission-oriented program, aka moonshot
 - Examples: Human Genome Project (a role model for BI)
 - Goal of HGP: Sequence DNA bases in the human genome
- Goal of BI: Map the human brain
 - Suggested as a scientific bottleneck by leading neuroscientists
 - Essential to understand the roots of brain disorders
 - Wider contributions— brain-computer interface, medical devices, prosthetics with sensory feedback
 - Funded research, hiring PhD and postdocs, development of tools and open data toward the goal
- BI is a multi-agency collaboration, including NIH, NSF, DARPA, FDA, and IARPA ($\geq$ \$5B in funding BI between 2013 and 2022)

Overview of Findings

- Post-BI and relative to the control groups, Neurotech startups:
 - Extensive margin: higher probability of receiving VC
 - Intensive margin: (i) Larger VC financing amount (ii) higher valuations (iii) quicker and more successful exits
- BI reduced technical uncertainty in neuroscience through:
 - Supplying skilled labor: More academic as inventors or early employees
 - Supplying science: significant contributions to the commercialization of neuroscience
 - Neurotech companies file for more and better patents
 - Knowledge spillover from complementary fields (AI and Big Data)

Data and Sample

- **VC and Startups:** Pitchbook; **Scientists:** Revelio Labs (LinkedIn); **Patents:** USPTO, KPSS **Grants and Publications:** NIH, NSF, BI website, Scopus
- Identification of Neuro-startups via patents
 - Any startup with a patent with a CPC containing *neuro, brain, nerve, optogenetics, Parkinson, Alzheimer, dementia*
 - Alternative Classification: PB Business Description and keywords
- 2000 to 2019: Treated: 755 Neuro, **Controls:** 49735 Any VC-backed, 8909 Healthcare; 9,409 Patenting

Relevance: Measuring BI's Commercial Applications

1. # patents citing an academic article (Marx & Fuegi, 2020)
2. Ex-ante citation prediction (Masclans-Armengol et al, 2024)

Citations

- Citations may underestimate the effect of BI
 - Truncation issue as the BI occurs in the recent half of the sample
 - Basic science R&D has foundational contributions, which direct pat-pub citations may not reflect
 - Discoveries, such as the fundamentals of how the brain works, are not patentable.
 - Patents do not cite the tools developed under the program
 - Machine learning can help overcome such limitations (Toole, Pairolero, Forman, and Giczy, 2020; Lerner and Seru, 2021)
3. We fine-tune a SciBERT model to determine which patents were influenced by BI knowledge (66% of all neuro patents) LLM

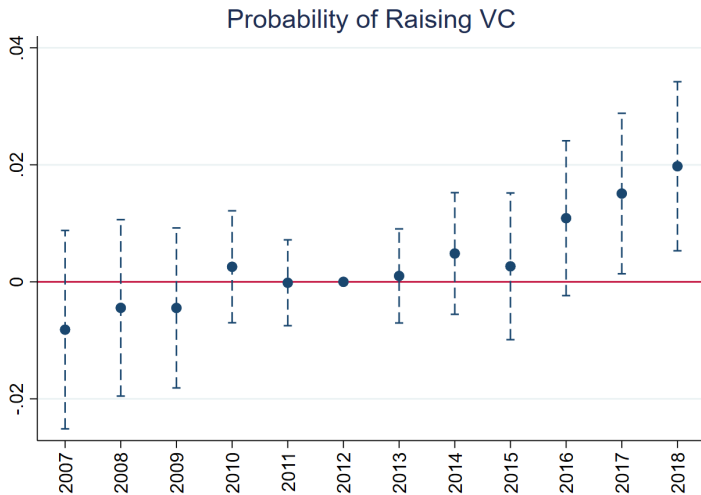
Baseline Results: VC Financing and Exit

Probability of Raising VC among Patenting Startups

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

	Received_VC			
	All Years		2007-2018	
	(1)	(2)	(3)	(4)
Neuro×Post	0.023*** (3.44)	0.022*** (3.34)	0.015*** (2.60)	0.015** (2.55)
Ln(Firm Age)		0.062*** (34.50)		0.067*** (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

Dynamic DiD: Probability of VC



VC Financing Amount

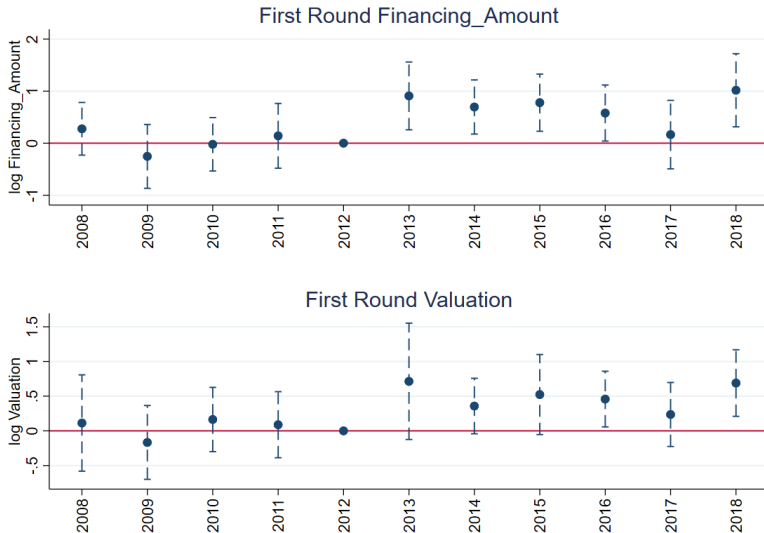
$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t + \beta_2 \text{Neuro}_i + \beta_3 X_{it} + \tau_t + v_{ijt},$$

	First Rounds				All Rounds			
	All	Healthcare	Patenting		All	Healthcare	Patenting	
			[08-17]				[08-17]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neuro×Post	0.495*** (5.07)	0.392*** (3.33)	0.309*** (4.08)	0.318*** (3.17)	0.287*** (4.29)	0.221*** (3.28)	0.225*** (2.97)	0.147** (2.22)
Neuro	0.079 (1.26)	0.119* (3.92)	0.350*** (5.38)	0.029 (0.44)	0.101** (1.97)	0.113** (2.15)	0.168*** (2.61)	0.107** (2.09)
Ln(# investors)	0.370*** (49.38)	0.542*** (24.55)	0.745*** (46.59)	0.433*** (24.81)	0.613*** (107.18)	0.763*** (60.01)	0.683*** (39.69)	0.711*** (67.16)
Observations	39586	7995	4873	8564	106576	23737	12567	31194
Adj R-squared	0.173	0.203	0.140	0.175	0.365	0.371	0.331	0.384
Mean Outcome	0.579	0.858	1.255	0.937	1.285	1.491	1.255	1.725
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
VC Round FE	N	N	N	N	Y	Y	Y	Y

Results: VC Valuation

	First Rounds				All Rounds			
	All	Healthcare	Patenting		All	Healthcare	Patenting	
			[08-17]				[08-17]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neuro×Post	0.358*** (3.48)	0.410*** (3.16)	0.397** (2.57)	0.228** (2.11)	0.241*** (2.74)	0.239*** (2.76)	0.202** (2.29)	0.106 (1.21)
Neuro	-0.006 (-0.09)	0.042 (-0.44)	0.028 (0.25)	0.024 (0.34)	0.132** (2.06)	0.052 (0.79)	0.126 (1.62)	0.193*** (3.00)
Ln(# investors)	0.187*** (21.97)	0.239*** (11.44)	0.382*** (19.24)	0.174*** (9.48)	0.340*** (46.81)	0.306*** (21.10)	0.235*** (12.14)	0.382*** (28.11)
Observations	19599	4206	2506	5127	60739	13612	7126	20218
Mean Outcome	1.778	1.863	2.718	1.938	2.918	2.957	2.718	3.265
Adj R-squared	0.084	0.087	0.129	0.093	0.491	0.462	0.432	0.500
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
VC Round FE	N	N	N	N	Y	Y	Y	Y

Dynamic DiD



Listed firms' neuro patents

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

Exposure to the BI: Labor, Patent influence, Geography

	Ln(Investment Size)			Ln(Valuation)		
	(1)	(2)	(3)	(4)	(5)	(6)
Employee_Exposure	0.696*** (3.03)			0.868*** (3.38)		
Ln(Patent_Exposure+1)		0.249** (2.47)			0.082 (0.88)	
Ln(State_Exposure+1)			0.254*** (4.89)			0.174*** (2.81)
Ln(# Investors)	0.758*** (17.58)	0.804*** (15.06)	0.794*** (19.23)	0.343*** (7.02)	0.422*** (6.50)	0.355*** (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

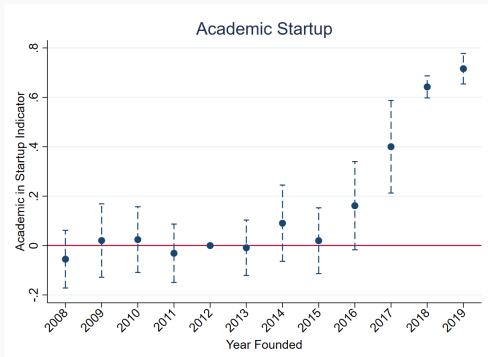
Exit outcomes: success and duration of the investment

	Successful Exit				Ln(Time to Exit)			
	All	Patenting	Healthcare		All	Patenting	Healthcare	
			[08-18]				[08-18]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neuro×Post	0.128*** (3.22)	0.121*** (3.13)	0.087** (2.20)	0.103** (2.17)	-0.256*** (-4.19)	-0.116* (-1.91)	-0.182*** (-2.84)	-0.151** (-2.11)
Neuro	0.071*** (2.79)	0.007 (0.27)	0.054** (2.12)	0.042 (1.18)	0.216*** (6.17)	0.035 (0.97)	0.203*** (5.39)	0.164*** (3.56)
Ln(Raised before exit)	0.065*** (56.44)	0.106*** (36.90)	0.100*** (38.48)	0.099*** (31.17)	0.078*** (42.83)	0.053*** (13.83)	0.046*** (11.12)	0.048*** (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

Mechanisms:
Human Capital
Innovation
Spillovers

Mechanism 1: Human Capital: Academic Startups

- Team's quality is a significant factor in startup funding (Bernstein et al. 2018)



Dynamic DiD estimates for Academic Startups: Neuro vs Other Healthcare

- Academics with secured jobs face a high opportunity cost of switching to the non-diversifiable risk of entrepreneurship (Hall and Woodward, 2010)

Mechanism 2: Innovation: Neuro Startup's Innovation

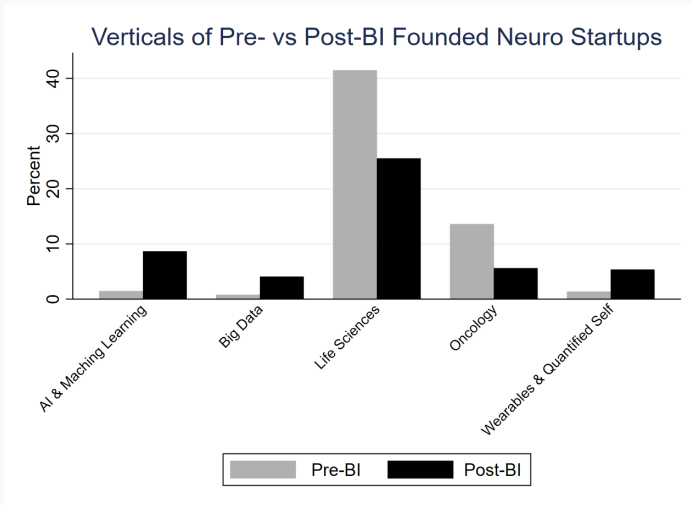
$$Y_{it} = \beta_1 \text{Neuro}_i \times \text{Post}_t + \beta_2 X_{it} + \lambda_i + \theta_t + \epsilon_{it}$$

	# 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 (3.248)***	0.510 (4.481)***	0.657 (5.276)***	0.661 (5.751)***	0.726 (3.752)***	0.762 (3.606)***	0.981 (6.253)***	0.824 (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

Mechanism 3: Spillovers from Complementary fields

- The brain comprises 86B neurons, forming 100T connections
- Mapping this network requires interdisciplinary research
- BI pooled neuroscientists with computer scientists, electrical engineers, mathematicians, etc.
 - BI grants are 3X more likely to include a data science keyword (e.g. Python, machine learning, AI, large datasets, etc)
 - data sharing, computational infrastructure
 - Google has developed computational tools for managing one of the BI datasets (25K terabytes)

Neurospace before and after the BI



- Industries

Integration with Complementary Technologies (AI, IoT, Smart wearables, Robotics)

	Complementary Technologies			
	All		Healthcare	
	[08-17]		[08-17]	
	(1)	(2)	(3)	(4)
Neuro × Post	0.068** (2.21)	0.094*** (2.77)	0.051* (1.65)	0.092*** (2.76)
Neuro	0.040*** (4.14)	0.015 (0.81)	0.003 (0.41)	-0.032** (-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

Conclusion

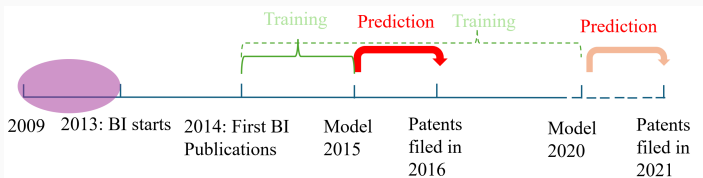
- The results suggest that markets might be constrained by scientific/technological bottlenecks
- We show that mission-oriented public investments can direct VC investments
- The US venture capital industry does not operate in a vacuum, and scientific institutions (NIH or NSF) are essential for its success

Mechanism 2: Innovation: Measures of commercial potential

Panel A: Patent citations of publications (Marx and Fuegi, 2020)			
	(1) #Citations	(2) #Citations	(3) #Citations
BI Publication	2.022 (0.301)***	1.192 (0.307)***	1.485 (0.301)***
NIH Non-BI			0.428 (0.056)***
Commercial Potential			4.361 (0.065)***
Scientific Potential			0.383 (0.052)***
Observations	2,274,602	83,838	2,274,602
Year FE	Y	Y	Y
Panel B: Commercial Potential (Masclans-Armengol et al, 2024)			
	BI Grant (A)	Non-BI pubs 2014 (B)	(A-B)
Commercial Potential	0.78	0.69	0.09***
	Non-BI pubs 2014 (B)	Non-BI from 2007 to 2013 (C)	(B-C)
Commercial Potential	0.69	0.64	0.05***

Mechanism 2: Innovation: patents influenced by the BI

- We employ SciBERT, an LLM, fine-tuned for understanding scientific text



- For every year $2015 \leq T \leq 2020$ we develop a LLM model:
 - Training dataset Positive: Publications from BI grants between 2014 and T
 - Negative: Publications from non-BI neuroscience grants between 2009 and 2013
- All models achieve an F1-score greater than 0.9
- 66% of all neuro patents that startups own are influenced by the BI research BI influence

What business are acquirers of neuro startups in?

Acquirer Sector	Neuro Startups				Other Healthcare Startups			
	Pre-BI		Post-BI		Pre-BI		Post-BI	
	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
Healthcare	30	93.75	142	89.31	740	87.89	861	86.97
IT	2	6.25	7	4.4	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		842		990	

- Verticals