The spatial distribution of public support for AI research

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Abstract:

A spatial distributional analysis of the population of Phase II research projects funded by the US SBIR program in FY 2020 shows differences across states in projects focused on artificial intelligence (AI). AI is a relatively new research field, and this paper contributes to a better understanding of government support for such research. We find that AI projects are concentrated in states with complementary AI research resources available from universities nationally ranked in terms of their own AI research. To achieve a more diverse spatial distribution of AI-related technology development, the availability of complementary AI research resources must be expanded. We suggest that the National Science Foundation's National AI Research Institutes represents an important step in this direction.

Keywords: artificial intelligence (ai) | public-sector program management | small business innovation research (SBIR) | agglomeration | university research

Article:

1. Introduction

The term artificial intelligence (AI) is defined by the National Artificial Intelligence Initiative Act of 2020 (Public Law 116–283):

> The term 'artificial intelligence' means a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. Artificial intelligence systems use machine and human-based inputs to—(A) perceive real and virtual environments; (B) abstract such perceptions into models through analysis in an automated manner; and (C) use model inference to formulate options for information or action.

The Congressional Research Service, in fulfillment of its mission to 'serve Congress with the highest quality of research, analysis, information and confidential consultation to support the exercise of its legislative, representational and oversight duties in its role as a coequal branch of government',1 has recently reported to Congress (Harris 2021: i) that: 'AI holds potential benefits and opportunities, but also challenges and pitfalls'. On the 'benefits and opportunities' side, AI offers a platform to provide insight into activities ranging from data processing to the enhancement of human activities involved in the optimization of the performance of systems. On the 'challenges and pitfalls' side, there are societal as well as ethical issues associated with the use of AI.2

From an economics perspective, there is little systematic evidence linking the performance consequences stemming from AI research to the cost of the AI research due in part to a lack of relevant data. Before such relationships can begin to be understood, much less quantified, it is important, if not imperative, to understand the sources of funding to support AI research, the objectives of the supported research, the characteristics of economic agents performing such research, and the spatial dimensions of where such research is taking place. As we discuss below, the extant literature is limited on systematic analyses that address the allocation of public research support specific to AI at any level of aggregation, although public research support to small firms across technologies through the US Small Business Innovation Research (SBIR) program has long been studied. This paper contributes to this needed body of knowledge through a descriptive analysis of several dimensions of publicly supported AI research.

The remainder of the paper is organized as follows. In Section 2, to provide context for this study, we briefly describe several milestone events in the development of AI technology from a US perspective. In Section 3, we focus on US public-sector support of AI research using public domain data on the population of small firms that received research support through the SBIR program in fiscal year (FY) 2020. In Section 4, we present a descriptive distributional analysis of the FY 2020 population [our emphasis] of SBIR-funded AI research activity across states, and we find that the spatial distribution is related to the availability of complementary university AI research resources within states. Finally, we conclude the paper in Section 5 with a summary of our analysis, we offer some policy implications from our findings, and we suggest a policy-related roadmap for future research related to the social dimensions of AI research.

2. Milestone events in the development of AI technology

In 1955, the RAND Corporation funded Allen Newell, Cliff Shaw, and Herbert Simon to develop a computer program to solve problems using the skills of humans. The program was called the Logic Theorist.3 It was presented to the US research community in the summer of 1956 at a conference at Dartmouth College in New Hampshire, hosted by John McCarthy and Marvin Minsky. The purpose of the conference was to:4

> … discuss seminal ideas on an emerging branch of computing called artificial intelligence, or AI. They imagined a world in which 'machines use language, form abstractions and concepts, solve the kinds of problems now reserved for humans, and improve themselves'. This historic meeting set the stage for decades of government and industry research in AI.

AI technology developed rapidly over the next two decades as computer technology improved in terms of its ability to store large amounts of information and to process it quickly. In 1970, Minsky gave an interview to Life Magazine in which he is quoted to have said: '[F]rom three to eight years we will have a machine with the general intelligence of an average human being'.5

The 1980s were characterized by two trends. The first trend was the expansion of machine learning algorithms, and the second was the increase in public funding for AI research. In the 1990s, the application of AI was further demonstrated through, for example, games:6

> In 1997, reigning world chess champion and grand master Gary Kasparov was defeated by IBM's Deep Blue, a chess playing computer program. This highly publicized match was the first time a reigning world chess champion lost to a computer and served as a huge step towards an artificially intelligent decisionmaking program.

In the current decade, one hallmark example of the evolved power of AI is seen in such applications as driverless cars.

3. SBIR support of AI research

The SBIR program was established through the Small Business Act of 1953 (Public Law 85–536). The purpose of the program was and still is to use small firms (defined as having 500 or fewer employees) as vehicles for stimulating technological advancement and hence economic growth. The SBIR program is a set-aside program; any federal agency with a current (in 2021) extramural research budget in excess of $100 million is required to set aside 3.2 percent of that budget to fund research in small firms7 Eleven federal agencies currently participate in the SBIR program.8

The SBIR program funds Phase I and Phase II projects. Phase I projects are typically 6-month proof of concept research projects, and they are legislatively funded at present at no more than $150,000. Phase II projects are typically 2-year projects aimed at the development of a new technology, and they are legislatively funded at present at no more than $1 million. However, there are exceptions to these award amounts as explained by Gallo (2021: 5):

> [A]gencies may request a waiver from the SBA [Small Business Administration] to exceed the Phase II award [and Phase I award] guideline by more than 50% for a specific topic … Agencies may make a sequential Phase II award to continue the work of an initial Phase II award. The amount of a sequential Phase II award is subject to the same Phase II award guideline and agencies' authority to exceed the guideline by up to 50%. Thus, agencies may award up to $3 million, adjusted for inflation, in Phase II awards for a particular project to a single recipient at the agency's discretion, and potentially more if the agency requests and receives a waiver from the SBA.

Table 1 shows for FY 2020, the most recent complete fiscal year for which SBIR award data are publicly available from the Small Business Administration, the population of Phase II research awards.9 The Department of Defense (DOD) is the largest SBIR participating agency accounting for 49 percent of total Phase II research support in FY 2020. And the total Phase II award amounts by DOD in FY 2020 are nearly twice that of the second largest SBIR participating agency, the National Institutes of Health.

Table 1. Distribution of Phase II SBIR total awards in FY 2020 by funding agency.

Funding agency (by total award amount)	Number of project abstracts	Total award amount ($000)
Department of Defense	982	$928,664.00
National Institutes of Health	487	$480,479.10
Department of Energy	197	$214,272.10
National Aeronautics and Space Administration	141	$116,319.10
National Science Foundation	115	$95,957.80
US Department of Agriculture	29	$18,197.20
Department of Homeland Security	12	$11,925.90
Department of Education	8	$7,163.50
Department of Transportation	12	$4,647.90
Department of Commerce	8	$3,200.00
Environmental Protection Agency	10	$2,992.70
Total	2,001	$1,883,819.20

Source: https://www.sbir.gov/sbirsearch/award/all.

To define a Phase II project as being focused on AI, we followed the methodology developed by the OECD through its AI Policy Observatory (e.g. Squicciarini and Nachtigall 2021).10 Specifically, we identified, with the assistance of OECD researchers,11 a Phase II project as being AI focused if at least one of the following keywords was present in the project's published abstract: AI and/or artificial intelligence, machine learning,12python,13 and data mining.14

Table 2 shows the number of AI-focused Phase II projects and the percentage of so-defined projects by funding agency; 9.4 percent of SBIR-funded Phase II projects are focused on AI or about 1 in 11 projects.15 Across-agency differences in the number (Column (2)) and percentage of AI-focused Phase II projects (Column (3)) reflect differences in the research emphasis of the funding agency and the research priorities of its program(s).

Table 2. Number of AI-focused Phase II projects, by agency.

Funding agency (by total award amount from Table 1)	(1) Number of Phase II projects	(2) Number of AI-focused projects	(3) Percentage of Phase II projects that are AI focused
Department of Defense	982	124	12.60%
National Institutes of Health	487	21	4.30%
Department of Energy	197	10	5.10%
National Aeronautics and Space Administration	141	10	7.10%
National Science Foundation	115	13	11.30%
US Department of Agriculture	29	0	0%
Department of Homeland Security	12	4	33.30%
Department of Education	8	0	0%
Department of Transportation	12	2	16.70%
Department of Commerce	8	2	25.00%
Environmental Protection Agency	10	1	10.00%
Total	2,001	187	Mean = 9.4%

Source: https://www.sbir.gov/sbirsearch/award/all.
Notes: The overall mean of 9.4% was calculated as (187/2001). Column (3) = Column (2)/Column (1).

Table 3 shows the award amounts to both non-AI-focused and AI-focused Phase II projects by funding agency. Not all SBIR agencies funded AI projects in FY 2020. On average, the cost of an AI-focused Phase II project is about 3.6 percent greater than for non-AI-focused Phase II projects. This percentage might be referred to by the term AI premium, as discussed below.16

Table 3. Phase II award amounts for non-AI-focused and AI-focused projects in FY 2020 by agency.

Funding agency (by total award amount from Table 1)	Average award for non-AI-focused projects (000s) (n = 1,814)	Average award for AI-focused projects (000s) (n = 187)
Department of Defense	$934.50	$1,022.90
National Institutes of Health	$990.70	$896.70
Department of Energy	$1,077.70	$1,274.70
National Aeronautics and Space Administration	$830.70	$749.50
National Science Foundation	$839.20	$797.00
US Department of Agriculture	$627.50	N/A
Department of Homeland Security	$995.30	$990.80
Department of Education	$895.40	N/A
Department of Transportation	$416.60	$241.10
Department of Commerce	$400.00	$400.00
Environmental Protection Agency	$299.20	$299.90
Overall Average	$938.30	$972.30

Source: https://www.sbir.gov/sbirsearch/award/all.

Note: The overall mean awards were calculated from the population of non-AI-focused and AI-focused projects.

4. Descriptive distributional analysis

Table 4 shows the distribution of non-AI-focused and AI-focused Phase II awards across the 50 US states, the District of Columbia (DC), and the territory of Puerto Rico (hereafter collectively referred to as the population of states). The AI premium varies across states. For example, in New Hampshire, the AI premium is negative, meaning that the average award amount for non-AI projects is greater than for AI projects; in California, the premium is 1.01 percent, meaning that the average award amounts for non-AI and AI projects are about the same; and in Indiana, the premium is 89.2 percent, meaning that the average award amount for AI projects in that state is much larger than for non-AI projects. The between-state variation in the AI premium is perhaps related to variation in the mix of agencies accounting for FY 2020 funding across states or to the scope or scale of the funded projects.

Table 5 shows the distribution of SBIR-funded Phase II projects and the distribution of SBIR-funded AI-focused Phase II project across states. Some states receive a greater number of Phase II projects than other states. The distribution of the number of SBIR-funded projects in Column (1) reflects the concentration of firms across states as well as other economic and possible political factors that are beyond the scope of this paper. Also shown in Table 5 in Column (2) is the distribution of AI-focused Phase II projects across states. Column (3) shows the percentage, within each state, of Phase II projects focused on AI (Column (2)/Column (1)). Across-state variations in these percentages are perhaps related to across-state variations in the mix of agencies accounting for the AI funding of the Phase II awards in Column (1). Finally, Column (4) shows the percentage of all 187 AI Phase II projects in FY 2020 being researched in each state (Column (2)/187).

Table 4. Distribution of Phase II non-AI-focused and AI-focused awards FY 2020 by state.

State / District of Columbia / Territory (alphabetical)	(1) Average award for AI-focused projects (000s) (n = 187)	(2) Average award for non-AI-focused projects (000s) (n = 1,814)
Alabama	$844.50	$924.8
Alaska	$0	$0
Arizona	$0	$887.50
Arkansas	$0	$913.10
California	$980.60	$970.50
Colorado	$848.50	$952.00
Connecticut	$0	$1,093.60
Delaware	$0	$673.30
District of Columbia	$1,499.80	$1,764.50
Florida	$0	$880.30
Georgia	$1,040.0	$972.7
Hawaii	$1,173.50	$916.20
Idaho	$0	$874.60
Illinois	$1,205.80	$900.40
Indiana	$1,497.90	$791.60
Iowa	$0	$741.00
Kansas	$0	$809.50
Kentucky	$0	$900.10
Louisiana	$0	$739.10
Maine	$989.10	$833.20
Maryland	$1,031.70	$973.00
Massachusetts	$990.50	$951.60
Michigan	$941.40	$949.50
Minnesota	$0	$825.20
Mississippi	$0	$1,000.00
Missouri	$399.70	$977.50
Montana	$0	$1,040.30
Nebraska	$0	$1,041.00
Nevada	$0	$966.90
New Hampshire	$299.60	$905.80
New Jersey	$854.10	$881.30
New Mexico	$500.00	$977.30
New York	$1,032.30	$1,030.60
North Carolina	$775.10	$861.00
North Dakota	$00	$00
Ohio	$1,032.90	$835.80
Oklahoma	$950.00	$640.10
Oregon	$1,600.00	$1,057.30
Pennsylvania	$819.60	$901.60
Puerto Rico	$0	$776.30
Rhode Island	$774.70	$804.50
South Carolina	$0	$816.50
South Dakota	$999.90	$960.90
Tennessee	$749.90	$835.80
Texas	$942.50	$928.10
Utah	$749.80	$1,014.30
Vermont	$0	$876.90
Virginia	$1,011.20	$938.00
Washington	$938.70	$837.20
West Virginia	$1,159.60	$2,003.00
Wisconsin	$0	$856.00
Wyoming	$0	$836.80
Overall Average	$972.30	$938.20

Source: https://www.sbir.gov/sbirsearch/award/all.

Table 5. Distribution of Phase II AI-focused projects in FY 2020 by state.

State / District of Columbia / Territory (alphabetical)	(1) Number of Phase II projects	(2) Number of AI-focused Phase II projects	(3) Percentage of Phase II projects focused on AI (within state)	(4) Percentage of total AI-focused Phase II projects (entire USA)
Alabama	33	2	6.1%	1.1%
Alaska	0	0	0%	0%
Arizona	32	0	0%	0%
Arkansas	7	0	0%	0%
California	411	46	11.2%	24.6%
Colorado	87	7	8.1%	3.7%
Connecticut	27	0	0%	0%
Delaware	8	0	0%	0%
District of Columbia	13	1	7.7%	0.5%
Florida	42	0	0%	0%
Georgia	27	2	7.4%	1.1%
Hawaii	17	2	11.8%	1.1%
Idaho	2	0	0%	0%
Illinois	43	5	11.6%	2.7%
Indiana	17	1	5.9%	0.5%
Iowa	11	0	0%	0%
Kansas	6	0	0%	0%
Kentucky	13	0	0%	0%
Louisiana	9	0	0%	0%
Maine	4	1	25.0%	0.5%
Maryland	97	12	12.4%	6.4%
Massachusetts	192	18	9.4%	9.6%
Michigan	37	2	5.4%	1.1%
Minnesota	30	0	0%	0%
Mississippi	1	0	0%	0%
Missouri	16	1	6.3%	0.5%
Montana	6	0	0%	0%
Nebraska	3	0	0%	0%
Nevada	2	0	0%	0%
New Hampshire	33	1	3.0%	0.5%
New Jersey	41	3	7.3%	1.6%
New Mexico	11	1	9.1%	0.5%
New York	100	9	9.0%	4.8%
North Carolina	68	5	7.4%	2.7%
North Dakota	0	0	0%	0%
Ohio	77	9	11.7%	4.8%
Oklahoma	6	1	16.7%	0.5%
Oregon	22	1	4.6%	0.5%
Pennsylvania	85	7	8.2%	3.7%
Puerto Rico	2	0	0%	0%
Rhode Island	8	3	37.5%	1.6%
South Carolina	9	0	0%	0%
South Dakota	4	1	25.0%	0.5%
Tennessee	19	2	10.5%	1.1%
Texas	80	13	16.3%	7.0%
Utah	37	1	2.7%	0.5%
Vermont	8	0	0%	0%
Virginia	131	25	19.1%	13.4%
Washington	47	4	8.5%	2.1%
West Virginia	2	1	50.0%	0.5%
Wisconsin	13	0	0%	0%
Wyoming	5	0	0%	0%
	2,001	187	Mean = 9.4%	100%

Source: https://www.sbir.gov/sbirsearch/award/all.

Notes: The overall mean of 9.4% was calculated as (187/2001). Column (3) = Column (2)/Column (1). Column (4) = Column (2)/187.

The research question asked in this paper is: Why do AI funding and the number of AI-focused projects vary across states? Our hypothesis that the spatial distribution of these metrics is related to the presence of complementary university AI research resources across states. In other words, the agglomeration of Phase II SBIR funding in states with complementary university research resources reflects the funding to firms located in states with such universities.17

Merriam-Webster defines the term agglomeration as 'the action or process of collecting in a mass'; however, the term is commonly used in academic studies with reference to clustering within cities18 or to the clustering of firms.

The benefits of firms clustering in certain areas have traditionally been traced to the insight of Alfred Marshall who wrote in Principles of Economics (1890, Book IV, Chapter X, §3: 332):19

> When an industry has once chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighbourhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously.

And, Marshall built on the clustering theme in Industry and Trade (1920: 599):

> The broadest and in some respects most efficient forms of constructive cooperation are seen in a great industrial district where numerous specialized branches of industry have been welded almost automatically into an organic whole.

However, we hypothesize that the agglomeration of AI-focused Phase II awards—not of firms—reflects the likelihood that the recipient firm developing a new technology from its proposed Phase II project will be successful. Firms that receive SBIR awards are small, by legislative mandate, and they are often nascent in terms of their research ability and related resources. AI is certainly not a mature technology. We posit that an element in the decision to award an AI-focused Phase II award to a firm, especially a small firm, located in State A over a firm located in State B might be the availability of complementary AI research resources to a firm in State A compared to a firm in State B.20

With respect to the agglomeration of researching firms, as opposed to the agglomeration of public-sector research funds, which is relevant in this paper, there are contemporary examples of clustering and of related innovative behavior. Many of those examples are associated with the location of science and technology parks near universities, as well as the location of technology-based firms near star scientists and their home universities (Amoroso et al. 2020). There have been numerous reviews of these innovation-related phenomena in the literature. Perhaps one of the earliest reviews was by Audretsch (1998), and more recent reviews are by Goel et al. (2016), Fang (2020), Kekezi and Klaesson (2020), Rosenthal and Strange (2020), and Moretti (2021).21 However, these reviews, and others, have focused on well-established firms or mature technologies and their geographic relationship to complementary knowledge resources.

US News and World Report ranked US universities by the importance/quality of their AI research. The top 10 ranked universities, ranked from 1 through 10, are: Carnegie Mellon University (PA), Massachusetts Institute of Technology (MA), Stanford University (CA), University of California-Berkeley (CA), University of Washington (WA), Cornell University

(NY), Georgia Institute of Technology (GA), University of Illinois-Urbana-Champaign (IL), University of Texas-Austin (TX), and University of Michigan-Ann Arbor (MI).22

Table 6 shows a comparison of the descriptive distributional metrics discussed above in states with and without a top 10 AI research university. We conclude from Table 6 that whether the recipient firm is in a state with a top 10 AI research university or not does make an economic difference in the allocation of Phase II SBIR project funding.23 In particular, states with a top10 AI research university have, on average, more AI-focused Phase II projects, a larger percentage of all state-based Phase II projects that are focused on AI, and a larger percentage of all state-based AI-focused projects.24

Table 6. Distribution of Phase II projects focused on AI in states with and without top 10 AI research universities.

Metric	States with no top 10 AI research university (n = 43)	States with a top 10 AI research university (n = 9)
Average number of AI-focused Phase II projects[a]	1.9	11.8
Average percentage of Phase II projects focused on AI[b]	6.7%	9.7%
Average percentage of total AI-focused Phase II projects[c]	1.1%	6.3%

a Calculated from Column (2) in Table 5.
b Calculated from Column (3) in Table 5.
c Calculated from Column (4) in Table 5.
Notes: States with a top 10 AI research university are California, Georgia, Illinois, Massachusetts Michigan, New York, Pennsylvania, Texas, and Washington.

5. Concluding remarks

This paper is based on the premise that the little empirical information about the performance consequences stemming from AI research is due to a lack of relevant data. And, to begin to understand the nature of AI research and its societal implications, it is important to understand the sources of funding to support AI research, characteristics of economic agents performing such research, and the spatial dimensions of where such research is taking place. The descriptive analysis above is but one step in that direction.

Our findings are that in FY 2020 public support of AI research in small firms is associated with the availability of complementary research resources to support the firms' AI-related technology development. One way to achieve a more diverse spatial distribution of AI-related technology development in small firms, and hence a more diverse spatial distribution of burgeoning technology platform expertise that affects both firm and regional economic growth, would be to expand the availability of complementary AI research resources across states. And, toward that end, the National Science Foundation has begun to do just that.

In FY 2020, the National Science Foundation established seven National AI Research Institutes. As stated in the National Artificial Intelligence Initiative Act of 2020, an institute is to be focused on:

> … a particular economic or social sector, including health, education, manufacturing, agriculture, security, energy, and environment, and [to include] a

> component that addresses the ethical, societal, safety, and security implications relevant to the application of artificial intelligence in that sector; or a cross-cutting challenge for artificial intelligence systems, including trust worthiness, or foundational science …25

Seven initial institutes were established in four of the states with a top 10 AI research university: California, Illinois, Massachusetts, and Texas.26 In FY 2021, 11 more new institutes were established and now each state with a top 10 AI research university has a National Science Foundation (NSF) institute.

This NSF policy response to the anticipated social benefits associated with the development of AI technology and its diffusion brings about the need for future research related to the estimation of the net social benefits associated with the use of supporting public research resources. Certainly, the net social benefits associated with the implementation of AI technology are varied not only over time but also over affected networks. Perhaps future NSF and/or Congressional initiatives to support AI research will include the establishment of centers to estimate such net social benefits through multiple case studies and to codify associated data.27

The newly constituted National AI Research Resource Task Force is charged with writing 'the road map for expanding access to critical resources and educational tools that will spur AI innovation and economic prosperity nationwide'.28 One important point that follows from the findings presented in this paper is that 'expanding access to critical resources … that will spur AI innovation' should consider the symbiotic relationship between firm AI-related resources and those resources that are accessible in and expandable from AI-focused research universities.

Conflict of interest statement.

None declared.

Endnotes

1. See, https://www.loc.gov/crsinfo/about/history.html.

2. One ethical issue is the use of AI for facial recognition. See, based on Harris (2021: 25), the Ethical Use of Facial Recognition Act (S. 3284); the Facial Recognition Technology Warrant Act of 2019 (S. 2878); the Facial, Analysis, Comparison, and Evaluation (FACE) Protection Act of 2019 (H.R. 4021); and the Commercial Facial Recognition Privacy Act of 2019 (S. 847).

3. See, https://sitn.hmsharvard.edu/flash/2017/history-artificial-intelligence/.\

4. See, https://www.ai.gov/about/. And see, https://250.dartmouth.edu/highlights/artificial-intelligence-ai-coined-dartmouth.

5. See, https://sitn.hmsharvard.edu/flash/2017/history-artificial-intelligence/.

6. See, https://sitn.hmsharvard.edu/flash/2017/history-artificial-intelligence/.

7. A detailed history of the SBIR program is in Link and Scott (2012) and Leyden and Link (2015).

8. The agencies are (alphabetically): the Departments of Agriculture (USDA), Commerce (DOC), Defense (DOD), Education (ED), Energy (DOE), National Institutes of Health (NIH)

within Health and Human Services, Transportation (DOT), Homeland Security (DHS); and the Environmental Protection Agency (EPA), National Aeronautics and Space Administration (NASA), and the National Science Foundation (NSF).

9. See, https://www.sbir.gov/sbirsearch/award/all.

10. See, https://www.oecd.ai/. See also, Chowdhury et al. (2021) and Giczy et al. (2021).

11. We thank Mariagrazia Squicciarini, former Senior Economist, Head of Unit at the OECD Directorate for Science Technology and Innovation (now at the UNESCO), for personal correspondences on OECD's protocols and for assistance in developing a US-specific list of defining keywords.

12. The National Artificial Intelligence Initiative Act of 2020 defines the term machine learning as follows: 'The term "machine learning" means an application of artificial intelligence that is characterized by providing systems the ability to automatically learn and improve on the basis of data or experience, without being explicitly programmed'. See, https://www.congress.gov/116/crpt/hrpt617/CRPT-116hrpt617.pdf#page=1210.

13. Python is a programming language.

14. Data mining refers to the process of identifying patterns in large datasets.

15. We thank an anonymous reviewer for emphasizing that the set of identified Phase II projects that are focused on AI is heterogeneous in the sense that some projects might be part of ongoing internal firm research related to AI and other projects might be nascent to the firm. We do not have detailed information on the scope of previous research for any of the FY2020 SBIR-funded Phase II firms.

16. We are using the word premium loosely to characterize the extent to which an award for an AI-focused project is greater than for a non-AI-focused project. In some agencies, the award amount for non-AI-focused projects is greater than for AI-focused projects as discussed below.

17. It should not be inferred from this statement that firms purposefully located in the to-be-defined states to increase the likelihood of receiving AI research funding. In all likelihood, a significant portion of the firms that received an AI-focused Phase II research awards in FY 2020 were already located in their current state.

18. See https://www.merriam-webster.com/dictionary/agglomeration. Merriam-Webster offer as a third definition of the term agglomeration the following: 'a large, densely and contiguously populated area consisting of a city and its suburbs.'

19. While the genesis of the economics benefits associated with agglomeration or clustering of firms is traditionally attributed to the insight of Marshall, the notion of information spillovers associated with juxtaposition per se traces at least to the Venetians in 1291. Johnson (2014: 14–17) documented that the fall of Constantinople in 1204 initiated the migration of many artisans. 'A small community of glassmakers from Turkey … settled into the canals and crooked streets of Venice [and] their skills at blowing glass quickly created a new luxury good for the merchants of the city to sell around the globe … The glassmakers had brought a new source of wealth to Venice, but they had also brought the less appealing habit of burning down the neighborhood'. In 1291, as a means of retaining the glassblowing industry in Venice as well as a means of protecting the city, glassmakers were exiled to the island of Murano, which was across the Venetian Lagoon. An 'innovation hub' had been created by chance. The juxtaposition of the

glassblowers ‘triggered a surge of creativity [and] the density of Murano meant that new ideas were quick to flow through the entire population [of artisans]’. See also, Link (2020) for contemporary examples of the impact of location on creativity and new ideas.

20. If one thinks of tacit knowledge as characterizing AI research, and if one thinks of the transportation of tacit knowledge having a cost, then one might point to the foundational scholarship of Weber (1929) and Hoover (1937) as being relevant. Weber and Hoover envisioned physical transportation costs as being a condition of agglomeration, but their insight is applicable to the transportation of tacit knowledge from AI research resources in selected universities to AI firms, especially to small AI firms that might not have sufficient technical capital.

21. There is also a rich literature that has also looked at the relationship between productivity and agglomeration. See, for example, Rosenthal and Strange (2004) and Andersson and Lööf (2011).

22. See, https://www.usnews.com/best-graduate-schools/top-science-schools/artificial-intelligence-rankings.

23. While our descriptive analysis is appropriate because our data relate to the population [our emphasis] of FY 2020 SBIR supported firms, we eschew an inferential analysis based on a model of the form Probability (AIproject) = f (Top10, X), where X accounts for agency fixed effects. Such an analysis would need to assume that FY 2020 is a sample [our emphasis] of previous and future fiscal years of SBIR funding of AI projects. However, the nature of AI technology is changing rapidly (Squicciarini and Nachtigall 2021), and thus FY 2020 may not representative of FY 2019, or earlier years, and likely not representative of FY 2021 and beyond.

24. Both the mean number of AI-focused projects and the mean percentage of total AI-focused Phase II projects are statistically different between states with and without a top 10 AI research university (in both cases, $P = 0.01$ under the assumption of equal variance and $P = 0.06$ under the assumption of unequal variance).

25. See, https://www.congress.gov/bill/116th-congress/house-bill/6216.

26. See, https://www.nsf.gov/news/ai/AI_map_interactive.pdf.

27. We refrain from making recommendations about other countries in which there have been private-sector and public-sector investments in AI. Simply, little is known about the context in which these investments are funded. With time, the OECD studies noted above will provide insight into international strategies and resulting outputs and outcomes.

28. See https://www.whitehouse.gov/ostp/news-updates/2021/06/10/the-biden-administration-launches-the-national-artificial-intelligence-research-resource-task-force/.

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