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We define Artificial Intelligence (AI) adoption in the United States in two ways:

- (1) Using the Census Bureau's 2018 Annual Business Survey, which provides adoption at the firm level, and
- (2) Using the near-universe of job postings, which provides a real-time measure of which workers and firms are using AI.

### AI Adoption

We analyze data from the Census Bureau's 2018 Annual Business Survey of over 850,000 firms to establish a number of stylized facts about early AI adoption in the U.S. While less than 6 percent of firms use any of the AI technologies we measure, adoption is prevalent in a subset of distinctive firms. At least some AI is used by most firms with over 5,000 employees. AI use is associated with owners who are more educated and experienced, yet also younger, and motivated by aspirations such as bringing new ideas to market or helping the community. Firms with early markers of high-growth entrepreneurship, that innovate, and that pursue growth-oriented strategies are also more likely to use AI. AI use is concentrated in a handful of "superstar" cities. In turn, AI is conditionally correlated with significant later-stage firm growth. The concentration and growth potential of AI's leading edge portend economic and social impacts far beyond this limited early diffusion, along with a potential "AI divide" if early patterns persist.

We characterize AI adoption patterns at the Core-Based Statistical Area (CBSA) level and find significant geographic disparity. We focus on single unit firms to pinpoint the exact location of AI use. The results are reported on maps in Figure 1. The bubble sizes represent the number of single-unit AI-using firms in the CBSA (weighted by employment), and the color gradient indicates the percentile rank of the CBSA in terms of the AI usage rate, while lighter colors correspond to higher rankings. Panel (a) in Figure 1 include all single-unit firms and Panel (b) focuses on young startups. Areas that are well known for pioneering technologies, such as Silicon Valley and Research Triangle, stand out as light yellow. Areas in the Northeast and Midwest have lower AI intensity as a share of the number of firms as indicated by the size of bubbles. Detailed and further discussions of our results can be found in our working paper, "AI Adoption in America: Who, What, and Where".

## AI Job Postings

Our focus is primarily centered on which firms and occupations request AI skills as highlighted within job postings. Grounded in the Lightcast (previously known as BGT) skills framework, we employ three distinct methodologies to define AI skills, each carrying slightly variant definitions.

The first methodology is based on the Deming and Noray (2020) Machine Learning and Artificial Intelligence categorization, incorporating 38 skills. Notably, this categorization encapsulates a wider spectrum of skills than those typically classified under Machine Learning. Examples include skills in Python, R, and Robotics. While one might argue that proficiency in a programming language like R does not equate to Machine Learning expertise, it is worth noting the scope for "minimal training". For instance, if an individual is capable of executing multiple regression tasks in Python using scikit-learn, they can feasibly transition to Machine Learning with relative ease.

The second approach relies on the Lightcast Machine Learning skill cluster which comprises 28 skills. This approach mirrors the methodology adopted by Acemoglu, Autor, Hazell, and Restrepo (2022). However, a limitation of this approach is its inability to include certain Machine Learning skills that are not classified within any skill cluster. An example of such an oversight would be Tensorflow, a library specifically used to conduct Machine Learning, yet absent from the Machine Learning skill cluster.

The third and final approach is featured in our forthcoming manuscript, "work2vec". Here, we examine the embeddings of the skills listed in the Machine Learning skill cluster and use this analysis to identify Machine Learning skills absent from the aforementioned skill cluster. We then look at the skills that have the greatest similarity and select the ones that suggest machine learning skills. This method identifies a total of 71 skills, 12 of which were not categorized within any skill cluster according to the BGT classification. Notably, Python and R are excluded from this list as they do not inherently constitute Machine Learning skills.

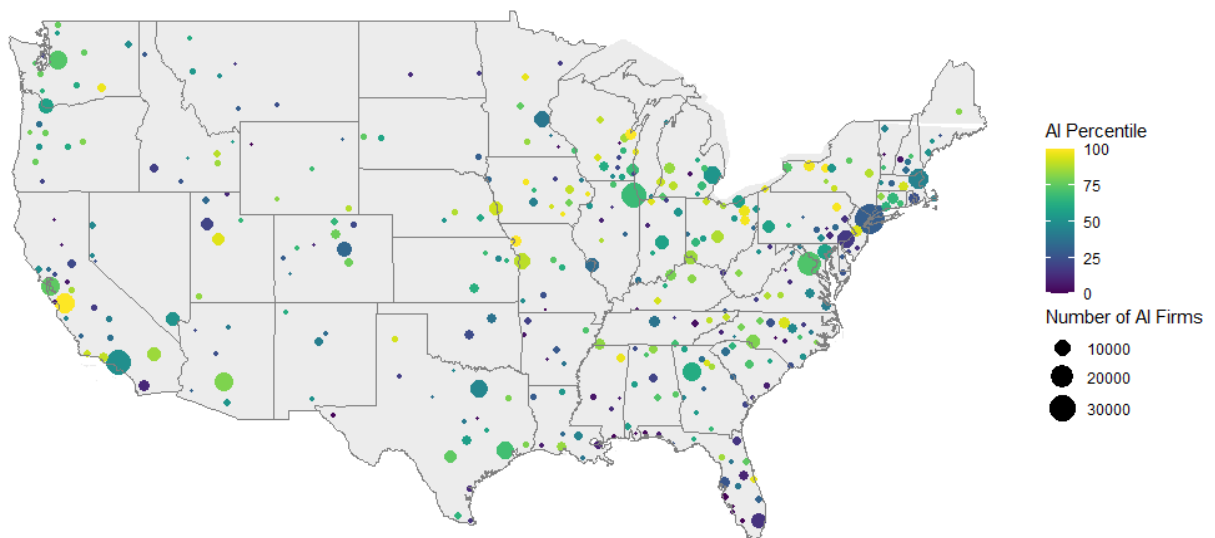
Using all approaches, AI related job postings are increasing significantly over time. The size of this increase depends on the specific measure: the broadest measure (Deming and Noray measure) shows the least percentage growth, from 1.4 percent in 2010 to 4.1 percent in 2022. The work2vec measure identifies 0.1 percent of job postings AI related in 2010, and 0.9 percent are AI related in 2022. This increase is even greater: almost a sevenfold increase.

## References

Acemoglu, Daron, Autor, David, Hazell, Jonathon and Restrepo, Pascual. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics*, 40 (S1).

David J Deming , Kadeem Noray, Earnings Dynamics, Changing Job Skills, and STEM Careers, *The Quarterly Journal of Economics*, Volume 135, Issue 4, November 2020, Pages 1965–2005, <https://doi.org/10.1093/qje/qjaa021>

Figure 1. AI Use Rates across Large CBSAs - Employment- weighted  
(a) All Single-Unit Firms



(b) Young Single-Unit Firms

