Policy Brief

The Race for U.S. Technical Talent

Can the DOD and DIB Compete?

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Executive Summary

Technical talent—individuals in computer and mathematical occupations who make up a large share of the AI workforce—is essential to U.S. innovation and growth. The mobility of this talent is also essential, as the movement of technical talent promotes the diffusion of ideas, expands professional networks, and spurs the development of innovative products. Attracting these highly mobile tech workers is therefore critical to staying on the cutting edge of the technological frontier. This is especially true for the defense community, which needs ready access to cutting-edge technologies and the workers who can design, develop, and deploy them. In the years ahead, understanding how this human capital flows within and between industry sectors is critical for maintaining U.S. technological leadership.

Conventional wisdom holds that the Department of Defense (DOD) and the defense industrial base (DIB)—collectively referred to as the defense community—generally struggle to access the technical talent they need. Countless studies and media reports detail the deficit of technical talent within the defense community, and the numerous risks associated with this shortfall. At the same time, there is a prevailing narrative that this talent is becoming increasingly concentrated in the so-called Big Tech firms, defined here as Facebook (Meta), Apple, Amazon, Netflix, Google (Alphabet), and Microsoft. Even amid the recent layoffs across the industry, these firms maintain a reputation for hiring large quantities of top technologists. However, little evidence is available to put these claims in perspective.

Our analysis seeks to illuminate trends in tech talent migration between different industry sectors and major metro areas, with the goal of informing future workforce development efforts across the defense community and the United States more broadly. We use data provided by Revelio Labs; specifically, LinkedIn positions based in the United States with start dates between 1998 and 2021. Our analysis validates some of the conventional wisdom and illuminates three major trends across the defense community's technical workforce:

1. **The defense community is not replacing or expanding its technical workforce at the same rate as other industry sectors.** For example, while the share of incoming versus outgoing workers was relatively equal for most sectors from 1998 through 2021, more than 75 percent of technical talent flows were outgoing for the DOD.

2. **The defense community remains relatively isolated from other sectors in terms of talent cross-flow and geographic hubs, which can slow technology adoption.** Additionally, tenures in the defense community tend to be longer than other industry sectors, which may also limit mobility and the sharing of innovative ideas and techniques.
3. **The U.S. Department of Defense recruits a relatively small share of its technical workforce from top-ranked computer science schools, an imperfect but commonly used proxy for quality**. Roughly 20 percent of the tech workers in the DOD between 1998 and 2021 held degrees from “ranked” universities, compared to more than 60 percent in the Big Tech firms.[1]

While none of these trends are necessarily problems in and of themselves, when taken together they can result in an environment that is not adequately equipped to recruit and retain talent, drive innovation, and adopt emerging technologies across the enterprise. We propose four recommendations for how the defense community can begin addressing these challenges and better access technical talent:

1. **Collaborate and partner as needed with the commercial software sector, promoting sectoral crossover and industry exchanges.**
2. **Invest in the human capital of the existing talent pool.**
3. **Investigate how to encourage the DOD and the DIB to become more integrated with the larger U.S. technical workforce.**
4. **Cultivate a future civil-service-minded technical workforce.**

Ultimately, the defense community has a sizable cadre of technical talent that must be appropriately identified and leveraged. Moreover, and equally important, the defense community has a critical role in growing and diversifying the domestic pipelines for future technical talent. Embracing both realities will go a long way to not only ensuring the DOD’s access to sufficient technical talent, but to positioning the United States for future global workforce competitiveness.

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Introduction

Technical talent is among the most important ingredients for success in the modern, knowledge-driven global economy. Understanding how this human capital flows within and between different industry sectors is critical for maintaining U.S. technological leadership in the years ahead. Increased mobility of technical talent promotes the diffusion of ideas, spurs innovation, and improves economic outcomes for the broader workforce.[2] The sectors that are able to attract these workers are thus better positioned to thrive in a tech-driven world.

The migration patterns of tech workers within the defense community are particularly important from a national security perspective. Emerging technologies such as artificial intelligence (AI) are playing an ever more important role in shaping the global security landscape, and the U.S. military needs a robust technical workforce to employ these innovations in an effective and responsible manner. This includes workers within the Department of Defense (DOD) itself as well as the broader defense industrial base (DIB), which is responsible for developing and maintaining much of the military's technology infrastructure.

For years, however, DOD leaders have voiced concerns about their ability to access tech workers across the department and broader DIB.[3] While major defense contractors employ a significant amount of technical talent, these companies face unique market forces that disincentivize investment in disruptive, unproven technologies. Given their relatively low profit margins, conservative corporate culture, and comparative advantage in building major platforms and systems, pursuing groundbreaking but risky projects related to emerging technologies such as AI does not always make good business sense.[4]

In recent years, military leaders have tried to address this gap by bringing more start-ups and commercially oriented vendors into their contractor pool. Working with nontraditional vendors—such as those coming to the DOD through the Defense Innovation Unit (DIU) and the National Security Innovation Network (NSIN)—has already enabled access to a broader pool of technical talent than is available through working with the major defense primes. However, driving more structural changes across the procurement ecosystem will require DOD leaders to rethink their approach to innovation.[5]

While prior research from the Center for Security and Emerging Technology (CSET) has examined the DOD's tech workforce and its efforts to engage nontraditional commercial vendors, few studies have examined the migration of workers between the defense community and nondefense industry sectors.[6] By understanding these talent flows, the DOD and DIB can more effectively pursue partnerships, target outreach efforts, and develop talent acquisition strategies.

This report explores the migration of technical talent with an emphasis on the defense community (DOD and DIB) and commercial software sector. Our analysis relies on several datasets: Revelio Labs, based on LinkedIn user profiles; U.S. Census data, to define metro areas; the *DefenseNews* Top 100 list, to help define the DIB; and a trio of university rankings for our assessment of education-based talent flows.

In addition to the DOD, DIB, and software industry, our analysis also examines talent migration patterns in three other economic sectors: finance, manufacturing, and management consulting. Like the defense community, finance and manufacturing struggle to compete with Big Tech and software technology firms for technical talent. Management consulting's rapidly expanding tech workforce and disproportionate overlap with the defense community made it worth including in our analysis. These industry sectors also provide a useful point of comparison due to differences in geographic distribution.

Our analysis explores technical talent migration through three different lenses:

1. **Industry concentration, churn, and cross-flow:** How are technical positions distributed across industry sectors? How do sectors compare in terms of worker inflow and outflow? How do workers move between sectors?
2. **Education:** What industry sectors are attracting the most tech workers with degrees from elite institutions?
3. **Geographic concentration:** Where are the greatest geographic concentrations of technical talent by industry sector?

Our report begins with an overview of the literature on talent flows and innovation, as well as an exploration of current labor market dynamics for technical talent in the United States. We then briefly describe the data used in our analysis and our methodology for defining industry sectors and geographies. Next, we detail our analysis of technical talent by industry sector and geography over time, as well as by educational institution ranking. Finally, we elaborate on findings that are relevant for the defense community, and offer recommendations to improve this community's access to tech talent going forward.

Talent Migration and Innovation

Talent migration is a critical driver of technological innovation. When workers move between jobs, they bring the knowledge, skills, and personal connections acquired over the course of their careers into new organizations and locations.[7] Through interactions with new colleagues, friends, and acquaintances, this knowledge spreads and recombines, resulting in novel ideas and greater innovation. The benefits of this intellectual intermingling is supported by the literature. Prior studies have found the most cited scientific papers and patents tend to blend knowledge from different disciplines in new ways, and researchers from different but related backgrounds are more likely to collaborate.[8]

This theory of innovation suggests that high worker mobility helps generate new ideas. A recent LinkedIn study found the software sector, which has produced some of the 21st century's greatest innovations, has the highest turnover rate of any industry sector.[9] Similarly, research has shown that Silicon Valley first established itself as an innovation hub because workers there changed employers far more frequently than other hubs of semiconductor design.[10] High worker mobility promotes entrepreneurship, skills development, and the transfer of social and financial capital—all of which empowers individuals to scale new ideas into viable businesses, products, and services.[11]

The migration of technical talent also shapes the geographic landscape of innovation. Regions and cities with high concentrations of human capital have historically encouraged more knowledge spillovers, allowed companies to assemble better teams, and provided a built-in market for new products and services.[12] In the United States, just 10 cities account for nearly half of the country's patents and one-third of its economic activity.[13] Prior CSET research found that U.S. AI workers are similarly concentrated in a handful of nationwide tech hubs, such as those centered around San Francisco, Seattle, Boston, and Washington, D.C.[14]

However, high employee churn is also disruptive, forcing companies to spend resources hiring new workers and potentially driving up wages. This has led to firms in the tech industry and other sectors using non-poaching agreements and other measures to prevent workers from leaving.[15] Striking the right balance between worker retention and churn is therefore essential to facilitating the spread of ideas and increasing productivity, particularly for firms in non-technology sectors.

Finally, although a significant body of literature links talent "clustering" to innovation, newer research suggests that technology may have eroded the importance of geographic proximity to innovation over time. The proliferation of the internet and improvements in remote collaboration tools have made it easier to work together and share knowledge, allowing organizations to access a more distributed and potentially higher-quality talent pool.[16] As a result, it has become relatively easier to generate innovative ideas outside of areas with high concentrations of talent.[17] While it falls outside the scope of this analysis, a better understanding of the relationship between remote work, knowledge spillovers, and talent clustering would empower business and government leaders to craft more effective workforce development strategies.[18]

Technical Talent Labor Market Trends

To understand the implications of our analysis for defense planners, we must consider our findings in the context of broader employment and economic trends. Our analysis is based on a sample of LinkedIn profiles, which makes it important to put our data in the context of official figures from the U.S. Bureau of Labor Statistics (BLS).

The integration of software and AI-enabled applications across every industry sector has made the need for technical talent ubiquitous. Every firm needs access to technical talent, whether contracted as a service or employed in-house.[19]

As a result, data, analytics, software, and AI talent (referred to as "technical talent" in this report) has been in high demand, with strong employment growth. Previous CSET research showed not only rapid growth in the technical talent workforce, but also that this segment of the workforce is projected to increase more than twice as fast as the national average.[20] (For the analysis of technical talent in this report, see the box below and Appendix A for a complete list of occupations.)

CSET's Definition of Technical Talent

Previous CSET research defined the AI workforce as "the set of occupations that include people who are qualified to work in AI or on an AI development team, or have the requisite knowledge, skills, and abilities (KSAs) such that they could work on an AI product or application with minor training." That definition purposefully included technical and nontechnical occupations that may not currently be working on AI applications, and binned AI-related occupations into four categories.

For this analysis, we consider only those employed in occupations in the category of "Technical Team 1": occupations that are or could be actively working in AI, are needed to provide technical inputs into AI applications, or could laterally move into an AI development role. This includes most computer and mathematical occupations. Moreover, since we include entire occupations, this definition captures a large share of data, analytics, software, and AI talent. (Examples: computer scientist, software developer, data scientist, network and database administrator.)

Table 1 shows employment in technical occupations grew much faster over 2012–2021 than all occupations.

Table 1. Growing Employment in Technical Team 1 Occupations*

	2012 Employment	2021 Employment	2012-2021 Percent Change
Technical Team 1	3,148,490	4,192,940	33.2%
Total U.S. Employment	130,287,700	140,886,310	8.1%

Source: Occupational Employment and Wage Statistics (OEWS), U.S. Bureau of Labor Statistics; CSET calculations.

Employment rates in key technology-centric industry sectors also increased rapidly over the last decade relative to other sectors studied in this report.[21] Table 2 shows that employment in software publishing doubled over 2011–2021, for example, with data hosting and processing and computer systems design increasing by about 50 percent. Meanwhile, employment in finance and insurance and manufacturing rose only modestly in comparison, and employment in the Department of Defense remained relatively flat. Interestingly, employment in technical and management consulting—a key provider of technical support to the federal government—also increased rapidly.

* 2011 estimates are not available. 2012 estimates are based on 2010 Standard Occupation Classification (SOC) codes while 2021 estimates are based on the 2018 SOC, which may be more precise. Estimates do not include self-employed workers.

Table 2. Total Employment and Shares, Selected Industry Sectors, 2011–2021

	Total Employment (Thousands)			Share of Total U.S. Employment*		Tech Talent Share† (2021)	
Industry Sector	2011	2021	% Change (2011–21)	2011	2021	Sector Share of Total Tech Talent	Tech Talent Share of Sector
Computer Systems Design	1,543	2,300	49%	1.2%	1.6%	26.7%	49.4%
Software Publishing	272	544	100%	0.2%	0.4%	5.4%	42.8%
Data Hosting/ Processing	246	388	58%	0.2%	0.3%	3.4%	37.1%
Technical/ Management Consulting	1,098	1,634	49%	0.8%	1.1%	3.6%	9.6%
Finance/ Insurance	5,769	6,519	13%	4.4%	4.5%	10.6%	7.3%
Federal Government	2,860	2,886	1%	2.2%	2.0%	2.7%	5.5%
Manufacturing	11,727	12,347	5%	8.9%	8.5%	7.0%	2.4%
DOD	559	564	1%	0.4%	0.4%	N/A	N/A
Total Employment	**131,922**	**146,102**	**11%**	**N/A**	**N/A**	**N/A**	**N/A**

Source: Current Employment Survey (CES) and Occupational Employment and Wage Statistics (OEWS), U.S. Bureau of Labor Statistics; CSET calculations.

The share of U.S. employment in key tech sectors—software publishing, data hosting and processing, and computer systems design—is also growing. Combined, the share

* 2011 and 2021 employment totals and respective total employment shares are based on the Current Employment Survey (CES). 2011 and 2021 employment shares are of total non-farm U.S. employment.

† "Sector Share of Total Tech Talent" is defined as the percentage of all workers classified as Technical Team 1 who are employed in each industry sector. E.g., 26.7 percent of all Technical Team 1 workers are employed in the Computer Systems Design sector. "Tech Talent Share of Sector" is defined as the percentage of the workers in each industry who are classified as Technical Team 1. E.g., 49.4 percent of the workers employed in the Computer Systems Design sector are classified as Technical Team 1. Based on Occupational Employment and Wage Statistics (OEWS survey), using 2021 employment totals for shares. 2011 data is not available for comparison.

of U.S. employment in software publishing, data processing and hosting, and computer systems design rose from about 1.6 percent in 2011 to 2.3 percent in 2021. Similarly, technical and management consulting increased from 0.8 percent to 1.1 percent. These are sizable increases, considering the share of employment in the federal government and in manufacturing fell over the last decade.

Still, we note that while there is much discussion about the criticality of these tech sectors, their share of U.S. employment remains small even as their market capitalization is enormous. Meanwhile, the share of total U.S. employment in finance and insurance and manufacturing were about 4.5 and 8.5 percent of total 2021 employment, respectively.

Table 2 also provides selected employment characteristics for key tech sectors and other sectors of interest for this report.[22] We include for comparison the 2021 share of total tech talent employment in the United States that is in that industry sector ("Sector Share of Total Tech Talent") and the 2021 share of industry sector employment that is technical talent ("Tech Talent Share of Sector"). For example, in 2021 computer systems design employed 26.7 percent of all U.S. technical talent. As a share of industry sector employment, technical talent comprised 49.4 percent of employment in computer systems design.

It is quite notable just how much of U.S. technical talent is employed in the key tech sectors studied here. Technical talent comprised between 37 and 49 percent of the employment in computer systems design, software publishing, and data hosting and processing in 2021. Other industry sectors studied here were not even close to those shares.

Moreover, when combined, computer systems design, software publishing, and data hosting and processing employ more than one-third of all technical talent in the United States. In contrast, in 2021 the federal government's workforce employed less than 3 percent of technical talent, and less than 4 percent of technical and management consulting—small shares relative to their size.

The high share of technical talent employed in key tech sectors makes these industry sectors distinct from those with lower shares in assessing labor market dynamics. For example, it is likely the high share of technical talent (and their respective strong bargaining power from high demand) are driving the large share of talent engaging in remote work across these industry sectors. According to the BLS, about 60 percent of workers in so-called "white-collar" occupations—including computer and engineering occupations—engaged in remote work in 2021, up markedly from pre-pandemic levels.[23]

While demand for technical talent has been strong, recent data suggests this could be abating, even if temporarily. [24] This is consistent with recent news media reports that also suggest the bargaining power for this talent may be weakening given recent economic conditions and a wave of layoffs.[25] That said, we note that even if overall employment declines and layoffs continue, it is likely that firms will disproportionately keep top performers core to their business model, reducing their mobility in the labor market.[26]

Finally, the concentration of U.S. market power for key players in the technology sector known as “Big Tech” or “FAANG+M”— Facebook (Meta), Apple, Amazon, Netflix, Google (Alphabet), and Microsoft—has increased markedly over the last decade.[27] Given the potential importance of these companies in the technical talent labor market, we analyze these companies separately in this report for additional insights on the technical talent ecosystem.

Methodology

This analysis focuses on technical talent spanning data, analytics, software, and AI talent, corresponding to "Technical Team 1" in previous CSET research defining the AI workforce. However, the dataset used for analysis—LinkedIn data provided by Revelio Labs—did not map directly on to our technical AI occupations.[28] This analysis therefore includes positions that are both in the United States and identifiable as likely being part of Technical Team 1 based on the following iterative process (a more detailed explanation can be found in Appendix A).[*]

1. **Identifying Technical Talent:** Revelio Labs assigns each position to one of 1,000 "work roles," using an unsupervised learning algorithm. After reviewing these roles and the positions assigned to them, we identified 111 roles that corresponded to our definition of "technical talent." In cases where the technical aspects of the role were ambiguous (e.g., development manager), we only included users that met certain educational requirements.

2. **Industry Sectors:** Each position in our dataset included the company and industry, as defined by LinkedIn's industrial categories. We grouped some of these industry sectors together thematically and also created three custom categories for sectors of particular interest: FAANG+M, DOD, and DIB.[29]

3. **Educational Ranking:** Individuals were categorized as having attended a "ranked" university if they received any degree from a university included in both the 2021 Academic Ranking of World Universities (ARWU) and the 2022 QS World University Rankings list of the top 500 global computer science programs.[30] Individuals who earned degrees from universities ranked in the top 10 places on *U.S. News and World Report*'s ranking of computer science graduate programs are categorized as "Ranked (Top 10)."[31] If the individual did not meet either the "Top-Ranked" or "Ranked" criteria but did have some type of non-empty educational information entered, they were considered "Unranked."

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[*] Throughout this analysis, we use the term "positions" to refer to roles held by tech workers, not open positions that they may be hired into. Prior CSET research has analyzed technical workforce trends using job postings. See: Diana Gehlhaus, Joanne Boisson, Sara Abdulla, Jacob Feldgoise, Luke Koslosky, and Dahlia Peterson, "China's AI Workforce," (Center for Security and Emerging Technology, 2022), https://cset.georgetown.edu/publication/chinas-ai-workforce/.

4. **Defining Location**: Our dataset included fields specifying the location and country of each position. We included only positions for which Revelio Labs identified the country as "United States" and mapped location data to Core-based Statistical Areas (CBSAs), a set of geographic areas defined by the Office of Management and Budget. The full list of CBSAs that we combined can be found in Appendix B.

Through this process, we identified approximately 14.5 million technical positions based in the United States. Roughly 12.6 million positions (87 percent) had a start date that fell within our selected time period (1998 to 2021). Of these positions with a valid start date, we were able to map roughly 12 million (95 percent) to a specific industry sector and 11.5 million (91 percent) to a U.S. metro area. Of the 6.4 million unique users that held U.S.-based technical positions, approximately 4.3 million (66 percent) included information on their postsecondary education (college attended and degree earned). More detailed information can be found in Appendix B.

While the dataset we relied upon for this report is extensive, it has some limitations. First, some of the data fields—such as location—were manually entered by the individual users without any enforced standardization or normalization. In addition to being as accurate as entered, it required intensive data aggregation and cleaning. Second, in some cases, data elements in the dataset were generated algorithmically. For example, Revelio Labs grouped the universe of job positions into 1,000 major groupings of similar types of jobs, some of which were ambiguous or overlapped. This required a degree of manual iterative review and adjudication. Finally, given the nature of who is on LinkedIn and differences in the type and quality of user-entered data, we must account for the possibility of bias in our analysis. While it is not possible to know the true bias on our results, several balance checks of our sample population suggested there is limited bias in geographic and industry reporting among the LinkedIn users in our dataset. A full discussion is in Appendix C.

Technical Talent Flows by Industry Sector

Understanding how technical talent flows to and from the defense community relative to the private sector is critical for crafting effective workforce policy. In this section, we examine how tech workers are distributed across industry sectors, how long they stay in their sector, and how they move within and between sectors.

Industry Sector Distribution

To understand how the U.S. tech workforce is distributed across the economy, we looked at the proportion of technical positions in each industry sector during different periods of time. This analysis is based on approximately 12 million U.S. technical positions in our data that included an industry classification and a start date between 1998 and 2021.

Table 3 shows the number of technical positions in different industry sectors by start date.[32] In every industry sector, the number of technical positions generally increased over time (although there is a notable downturn in new DOD positions between 2014 and 2021). Two factors likely drove this growth. The first is the proliferation of software, data analytics, and other digital technologies across the economy, which increased the demand for technical talent in virtually every sector. The second factor is the growing popularity of LinkedIn. The platform launched in 2002, and the expansion of its user base naturally increased the number of positions recorded on the site and, subsequently, in the Revelio Labs dataset.[33]

Table 3. Industry Sector Technical Positions by Start Date, 1998–2021

Industry Sector	1998–01	2002–05	2006-09	2010–13	2014–17	2018-21
DIB	42,231	57,858	80,688	95,172	126,043	147,321
DOD	19,909	28,784	42,048	51,122	47,673	29,405
FAANG+M	13,620	18,521	41,213	82,201	166,203	276,356
Finance	96,889	108,064	159,746	215,101	343,211	405,704
Management Consulting	5,106	6,083	10,632	18,789	33,129	49,437
Manufacturing	35,910	34,789	47,064	66,332	101,345	107,233
Software	278,371	295,747	480,518	713,936	988,948	1,043,788
Other Industries	410,962	421,555	657,645	932,108	1,292,643	1,320,309
Total New Positions	**902,998**	**971,401**	**1,519,554**	**2,174,761**	**3,099,195**	**3,379,553**

Source: CSET analysis of Revelio Labs data.

While the total number of new positions generally increased over time, different sectors experienced different levels of growth. Table 4 shows the share of technical positions in different industry sectors by start date. Between 1998 and 2021, the share of technical positions at the FAANG+M (Big Tech) companies increased more than fivefold, and the share in management consulting nearly tripled. The share of positions in the software sector—the largest employer of technical talent—remained relatively stable during this time, with the sector accounting for slightly less than one-third of new positions in each four-year period. The financial sector, another major employer of tech workers, also maintained a relatively consistent share of the tech workforce, except for a slight dip around the time of the Great Recession in 2007.

By contrast, both the DOD and DIB saw their share of the technical workforce drop during the same period. Both sectors expanded significantly in the immediate aftermath of the September 11th terrorist attacks, but their share of new positions steadily fell over time. From their peak in 2002–2005 to the most recent period, DIB saw its share of new technical positions fall from 6 percent to roughly 4 percent and DOD saw its share plummet from 3 percent to less than 1 percent. While this does not mean the defense community is losing technical talent, it does suggest the DOD and DIB are not expanding their technical workforce at the same rate as other sectors.

Table 4. Share of New Technical Positions by Industry Sector, 1998–2021

Industry Sector	1998–01	2002–05	2006–09	2010–13	2014–17	2018–21
DIB	4.7%	6.0%	5.3%	4.4%	4.1%	4.4%
DOD	2.2%	3.0%	2.8%	2.4%	1.5%	0.9%
FAANG+M	1.5%	1.9%	2.7%	3.8%	5.4%	8.2%
Finance	10.7%	11.1%	10.5%	9.9%	11.1%	12.0%
Management Consulting	0.6%	0.6%	0.7%	0.9%	1.1%	1.5%
Manufacturing	4.0%	3.6%	3.1%	3.1%	3.3%	3.2%
Software	30.8%	30.4%	31.6%	32.8%	31.9%	30.9%
Other Industries	45.5%	43.4%	43.3%	42.9%	41.7%	39.1%

Source: CSET analysis of Revelio Labs data.

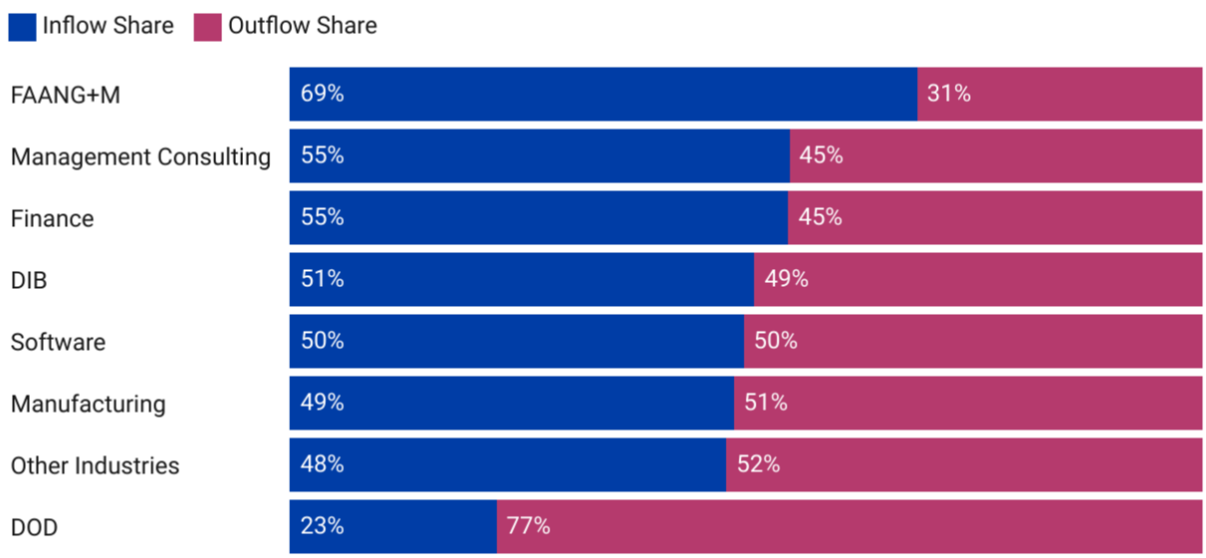
It is worth noting that the distribution of technical talent in the Revelio Labs data is in line with the BLS employment data outlined in Table 2. The Revelio Labs data shows approximately 39 percent of positions that began between 2018 and 2021 were in the software industry ("Software," and "FAANG+M"), while the BLS data shows that in 2021, about 36 percent of technical talent was employed in this sector ("Computer Systems Design," "Software Publishing," "Data Hosting + Processing"). The shares working in finance and manufacturing were also similar in both datasets.[34]

Industry Sector Churn

Another useful way to examine the strength of an industry sector's talent pipeline is by looking at the "churn" of workers within that sector. Here, we consider two different measures: 1) the rate of worker inflow relative to outflow, and 2) the average tenure of workers at companies in each industry sector.

Figure 1 compares the relative inflows and outflows of technical talent within each industry sector. While the shares of incoming versus outgoing workers are relatively equal for most sectors, there are two notable exceptions: the FAANG+M firms and the DOD. The number of workers joining the FAANG+M firms far exceeded the number who left, while the opposite was true for the DOD. These differences between worker inflows and outflows are consistent with the changes in industry distributions discussed in the prior section. The DOD's share of tech positions shrunk over time (net outflow) while the FAANG+M firms' share grew (net inflow).[35]

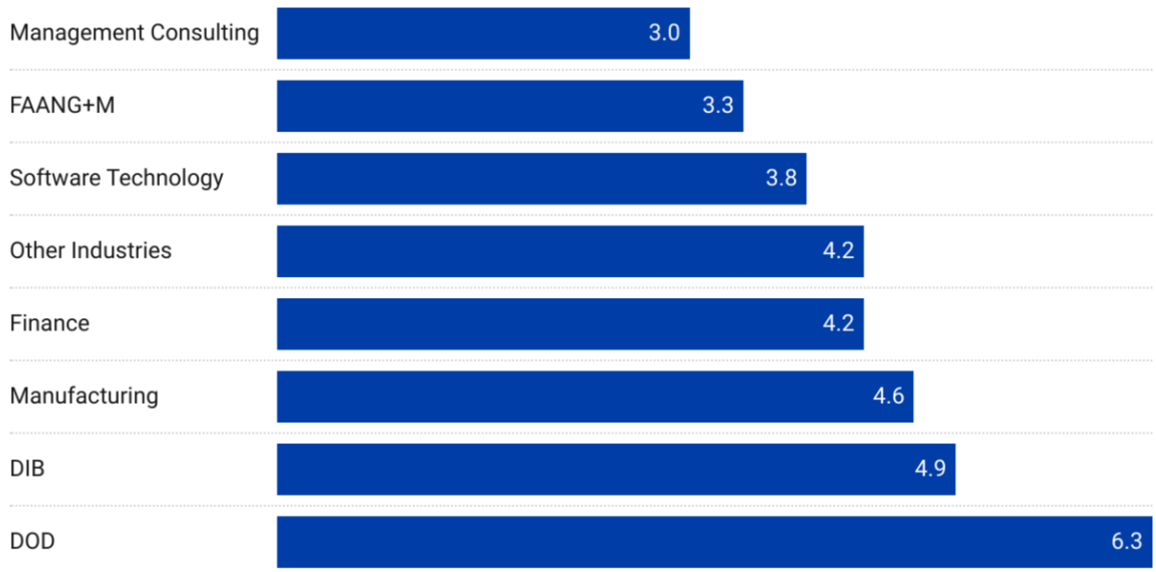
Figure 1. Share of Industry Sector Moves by Type, 1998–2021



Source: CSET analysis of Revelio Labs data for selected industry sectors.

Our analysis also suggests that technical talent employed by the DOD has much lower "churn" than their counterparts in other sectors. This means they are less likely to switch employers (non-DOD) over time. Figure 2 shows the average length of time that workers spend at companies in each industry sector. While workers at management consulting and FAANG+M firms spend roughly three years at their companies, technical talent in the defense community has much longer average tenures. Among the DOD's civilian workers, this tendency to stay in jobs longer may reflect a mindset prevalent across the public sector that encourages civil service as a lifelong career.[36]

Figure 2. Average Years Spent at Company by Industry Sector, 1998–2021



Source: CSET analysis of Revelio Labs data for selected industry sectors.

Although DOD workers' relatively long average tenure is not bad in and of itself, it can potentially slow the department's uptake of new technologies and processes. Employee turnover can ultimately introduce new ideas to an organization. The lengthy tenures within DOD, combined with the relatively low share of talent inflow, raises questions about the military's ability to infuse cutting-edge technologies and techniques into its operational culture.

By limiting potential talent inflow, a long security clearance process could also be limiting the uptake and adoption of emerging technologies. While the security clearance process is important for maintaining national security through responsible access to classified information, it comes with a well-known trade-off that could be reflected in our data: It is notoriously long and raises the barrier to entry for many national security jobs, which can disincentivize or altogether prohibit talented technologists from entering the defense community. Simultaneously, workers may be incentivized to continue working in the defense community once they have obtained this "credential" and may be reluctant to take on a role that would cause it to lapse.

Industry Sector Cross-Flow

In addition to sectoral labor market dynamics, we also examined the strength of technical talent flows between different pairs of industry sectors. Interindustry crossover helps spread ideas and business practices across the economy, making it a valuable mechanism for innovation.

Table 5 shows how the tech workers in our dataset moved within and between industry sectors between 1998 and 2021. Perhaps unsurprisingly, when moving jobs, workers often stay within their original sector rather than switch to a different industry sector. These “intra-industry” moves accounted for roughly 56 percent of the total moves in our dataset (see Appendix D for more information, including a chart for inflows and outflows with intra-industry moves counted separately).

Table 5. Movements Between Industry Sectors by Number of Positions, 1998–2021

		Destination							
		DIB	DOD	FAANG+M	Finance	Management Consulting	Manufacturing	Software	Other Industries
Origin	DIB	154,399	5,288	7,823	13,915	3,137	7,803	67,541	70,127
	DOD	19,443	59,604	1,525	3,806	955	1,562	22,533	25,968
	FAANG+M	1,810	167	200,511	8,076	952	1,830	56,182	40,146
	Finance	10,723	951	18,576	377,848	5,844	14,017	146,515	195,582
	Management Consulting	2,138	287	2,370	5,683	17,187	1,085	15,703	17,566
	Manufacturing	9,586	571	6,100	17,390	1,350	80,439	43,477	71,819
	Software	60,919	6,013	100,328	183,960	20,011	41,976	1,346,217	609,740
	Other Industries	77,542	8,840	103,056	238,044	21,942	73,655	658,284	1,829,958

Note: Workers are counted multiple times if they moved multiple times over 1998–2021.

Source: CSET analysis of Revelio Labs data for selected industry sectors.

Using position changes as an indicator of workers' migration trends, the data also reveals how closely different sectors are connected to one another. Table 6 shows the share of each sector's outgoing workers that arrive in different industry sectors. Given its size, the software sector is a top destination for tech workers leaving their industry sector. More than one-third of the workers who leave defense, finance, and management consulting positions—and more than half of those who depart positions from the FAANG+M (Big Tech) companies—wind up in the software sector. A sizable share of departing workers also make their way to other industry sectors that are not included in our analysis. The analysis also underscores the close ties between the DOD and DIB; more than a quarter of DOD workers move to the DIB after leaving the department.

Still, when taken on their own, these figures can sometimes obscure interesting underlying relationships between industry sectors. While it is notable that the software sector is a top destination for tech workers, this finding may not come as a surprise considering the sector has consistently accounted for more tech positions than any other industry sector since 1998 (see Table 4).

To analyze the strength of the connections between different sectors, it helps to compare talent flows relative to sector size. Say there are three sectors: Sector A, Sector B, and Sector C. If the connections between all three sectors were equally strong, we would expect to see workers leaving one sector distribute themselves across the other two sectors proportional to their share of the external talent pool. For example, if Sector B employs 3,000 workers and Sector C employs 1,000 workers, then if 100 workers left Sector A, we would see about 75 (three-quarters) go to Sector B and 25 (one-quarter) go to Sector C. However, if the outgoing workers from Sector A were evenly split between sectors B and C (50 going to each), that would suggest that the connection between sectors A and C is stronger than the connection between sectors A and B. Sector C received 50 percent of Sector A's outflow (outflow share), while it accounts for only 25 percent of the positions outside of Sector A (position share). By contrast, Sector B's outflow share (50 percent) was less than its position share (75 percent). While comparisons between observed outflow and talent share are imperfect, they can help illuminate interindustry connections in a way that unscaled cross-flow figures do not.

Table 6 is color-coded to reflect the differences between the distribution of outgoing workers from their origin industry sector and the distribution of positions across destination industry sectors. Relatively strong interindustry talent flows (outflow share > position share) are shaded blue, while relatively weak interindustry talent flows (outflow share < position share) are shaded red.

Our analysis revealed a particularly strong outflow of workers from the DOD to the DIB. Between 1998 and 2021, about 4.6 percent of non-DOD tech positions were in the DIB, but more than 25 percent of the tech workers who left the DOD went to the DIB—a fivefold increase over its position share. In addition to the DOD and DIB relationship, we also found relatively strong flows of workers from the DIB to management consulting, and from FAANG+M firms to other firms in the commercial software industry.

The data also suggests the defense community is more removed from the rest of the U.S. tech workforce. For instance, in our dataset the DOD accounts for roughly 1.9 percent of tech talent positions outside of the FAANG+M companies. But in the Revelio Labs data, less than 0.2 percent of workers leaving FAANG+M companies moved to positions in the department. Thus, the DOD’s share of the outflow from these companies is nearly 90 percent smaller than its equivalent share of technical positions. While this is the most extreme example, for every industry sector except the DIB, the outflow of workers into the DOD was lower than its proportion of the overall tech talent pool.

Table 6. Share of Outflow by Industry Sector, 1998–2021 (Rows Sum to 100 percent)

		Destination							
		DIB	DOD	FAANG+M	Finance	Management Consulting	Manufacturing	Software	Other Industries
Origin	DIB		3.0%	4.5%	7.9%	1.8%	4.4%	38.5%	39.9%
	DOD	25.7%		2.0%	5.0%	1.3%	2.1%	29.7%	34.3%
	FAANG+M	1.7%	0.2%		7.4%	0.9%	1.7%	51.5%	36.8%
	Finance	2.7%	0.2%	4.7%		1.5%	3.6%	37.4%	49.9%
	Management Consulting	4.8%	0.6%	5.3%	12.7%		2.4%	35.0%	39.2%
	Manufacturing	6.4%	0.4%	4.1%	11.6%	0.9%		28.9%	47.8%
	Software	6.0%	0.6%	9.8%	18.0%	2.0%	4.1%		59.6%
	Other Industries	6.6%	0.7%	8.7%	20.1%	1.9%	6.2%	55.7%	

Note: Figures represent the share of departing workers from the “Origin” industry sector who arrived in each “Destination” industry sector. For example, of all the technical workers who left the DOD for another industry sector, 25.7 percent took positions in the DIB.

Source: CSET analysis of Revelio Labs data for selected industry sectors.

We also find interesting trends when comparing the proportion of each industry sector's incoming workers that arrive from different sectors (inflow share) to position shares, as shown in Table 7. The software industry is a top supplier of talent to nearly every sector, accounting for more than one-third of workers who enter the management consulting and finance sectors, as well as DIB and FAANG+M firms.

This inflow analysis also underscores the strong ties between the DIB and DOD. More than 10 percent of the technical workers who enter the DIB come from the DOD, even though the DOD accounts for only about 2 percent of non-DIB tech positions. Similarly, nearly a quarter of tech workers who join the DOD previously held positions in the defense sector, though the DIB only accounts for about 4.6 percent of non-DOD tech positions.

This comparison of inflow share and position share also suggests the workers who hold positions within the FAANG+M ecosystem are generally slow to leave for other industry sectors. For example, the FAANG+M firms account for about 5 percent of tech positions outside the DOD, but only about 1 percent of positions moved into the DOD come from these companies. In fact, for every industry sector, the share of incoming workers from FAANG+M companies is lower than the firms' share of the overall tech talent pool. In other words, the firms "absorb" workers from other industry sectors (as shown in Table 7) but they do not "contribute" as many workers back to those sectors.[37] Once workers take jobs at these firms, they tend to stay at the company or bounce between other FAANG+M companies.

Table 7. Share of Inflow by Industry Sector, 1998–2021 (Columns Sum to 100 percent)

		Destination							
		DIB	DOD	FAANG+M	Finance	Management Consulting	Manufacturing	Software	Other Industries
Origin	DIB		23.9%	3.3%	3.0%	5.8%	5.5%	6.7%	6.8%
	DOD	10.7%		0.6%	0.8%	1.8%	1.1%	2.2%	2.5%
	FAANG+M	1.0%	0.8%		1.7%	1.8%	1.3%	5.6%	3.9%
	Finance	5.9%	4.3%	7.7%		10.8%	9.9%	14.5%	19.0%
	Management Consulting	1.2%	1.3%	1.0%	1.2%		0.8%	1.6%	1.7%
	Manufacturing	5.3%	2.6%	2.5%	3.7%	2.5%		4.3%	7.0%
	Software	33.4%	27.2%	41.8%	39.1%	36.9%	29.6%		59.1%
	Other Industries	42.6%	40.0%	43.0%	50.6%	40.5%	51.9%	65.2%	

Note: Figures represent the share of workers entering the "Destination" industry sector who came from each "Origin" industry sector. For example, of all the technical workers who entered the DOD from another industry sector, 23.9 percent came from the DIB.

Source: CSET analysis of Revelio Labs data for selected industry sectors.

Technical Talent Flows by Educational Ranking

Assessing the quality of an industry sector's technical workforce is essential for understanding the strength of its talent pipeline. There is no single way to objectively measure the quality of a particular worker, much less an entire industry sector's workforce. However, for the purposes of this brief, we explored how the educational background of technical workers—specifically, the rankings of the universities they attended—varies across industry sectors. While university rankings are an imperfect proxy for technical skills, recruiters—particularly at Big Tech firms—tend to use it as a heuristic for identifying top talent (see Box below).[38] This is in spite of these firms' advocacy for certificates, certifications, and other microcredentials—some of which they provide—to act as important alternative pathways into technical careers.[39]

The Quest for Exceptional Talent

There is significant debate within the technology industry about what constitutes "exceptional" talent. One prominent idea originates in a 1968 study that found a substantial variation in the effectiveness of the software written by software engineers, measured by technical factors such as the amount of computer memory used by their program.[40] Many in the industry believe that the success of most software products can be attributed to these "rockstar" or "10X" engineers. Bill Gates once remarked that "a great writer of software code is worth 10,000 times the price of an average software writer."[41] As Netflix explains in their culture guide, "Sustained 'B' performance … gets a severance package with respect," while Amazon insists that its managers should "raise the performance bar with every hire and promotion."[42]

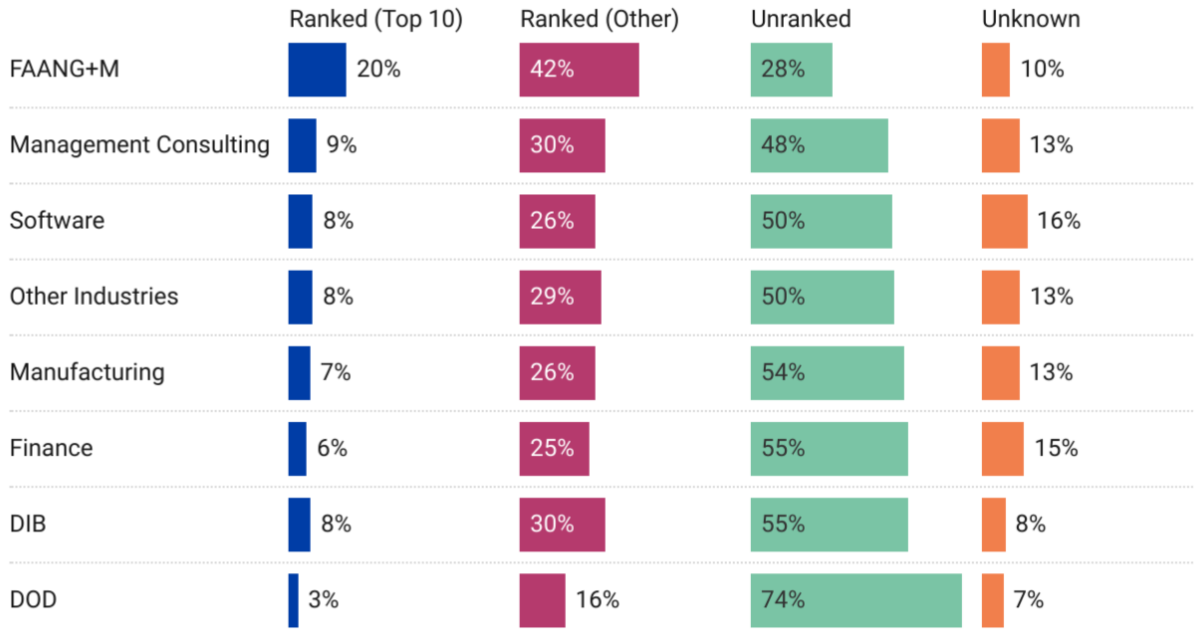
For our analysis, we divided tech workers into four groups based on their educational background:

1. **Ranked (Top 10):** individuals who hold a degree from a university that appears in the Top 10 of the *U.S. News & World Report* list of top computer science graduate programs[43]
2. **Ranked (Other):** individuals who hold a degree from a university that appears in both the 2021 Academic Ranking of World Universities (ARWU) and the 2022 QS World University Rankings (QS) list of the top 500 global computer science programs but not the *U.S. News* Top 10[44]

3. **Unranked:** individuals who hold a degree from a university that does not appear on both the ARWU and QS lists
4. **Unknown:** individuals who have no educational information recorded in the Revelio Labs dataset

Figure 3 shows how the educational background of employees in our dataset varies across industry sectors. While most industry sectors have relatively similar proportions of employees who graduated from top-ranked universities, two categories in particular stand out. First, the FAANG+M (Big Tech) firms notably hire a far greater percentage of individuals from ranked universities and from the most highly ranked universities. This is the only sector where a majority of its employees graduated from a ranked university. In contrast, the DOD employs fewer individuals who graduated from ranked computer science programs than any other sector in our analysis.[45] Only about one-fifth of DOD's technical staff graduated from a globally ranked university, and DOD positions included the fewest percentage of individuals who graduated from a top-ten computer science program.

Figure 3. Educational Institution Ranking of Technical Talent



Note: The military academies are not counted as ranked universities, as they appear in neither the ARWU or QS Top 500. Totals across rows do not always sum to exactly 100 percent due to rounding.

Source: CSET analysis of Revelio Labs data.

The data also demonstrates that most industry sectors have increased their share of employees who graduated from a ranked university over time. Comparing the educational background of employed technical staff in our dataset from 2010 to 2021 with equivalent data from 1998 to 2009 indicates that most industry sectors have increased their share of employees who graduated from a ranked university by between 4 and 7 percent. However, not every sector grew its share of technical talent with a stronger educational background. Three sectors in particular saw essentially no growth in this area: employees of the DOD, the DIB, and the federal government.

Technical Talent Flows by Geography

The geographic distribution and movement of technical talent is also relevant to understanding a country's innovation ecosystem. Regions with high concentrations of technical talent typically benefit from increased knowledge spillovers and lead the way in technology development and adoption.

Prior CSET research has found that the U.S. technical workforce is concentrated in a handful of major metro areas.[46] Our analysis of Revelio Labs data similarly shows concentration of talent in key hubs, but that these hubs vary widely across industry sectors.

Table 8 shows the top five metro areas for workers in each industry sector, as well as the share of each industry sector's technical talent pool that is concentrated in its top five and top ten metro areas. A few trends stand out. First, a significant share of workers employed in the commercial software sector are concentrated in "traditional" tech hubs such as San Francisco, Seattle, and New York City. These three cities are home to nearly 80 percent of tech workers at the FAANG+M firms, and more than 30 percent of those in the broader software sector. Some or all hubs also appear in the top five of most other sectors in our analysis, with DIB and DOD being notable exceptions.

However, the geographic distribution of tech workers in the defense community looks far different than that in the broader private sector. Both the DOD and DIB have Washington, D.C., as their top tech hub. While Washington D.C. appears in the top five for many other industry sectors, it is not nearly as prominent (with management consulting being the exception). Moreover, the other top defense hubs have little overlap with the top hubs of other sectors.

Table 8. Top Metro Areas for Tech Workers in Each Industry Sector, 2017–2021

DIB	
Washington, DC	17%
Los Angeles, CA	7%
Denver, CO	5%
San Diego, CA	4%
Dallas, TX	4%
Top 5 Metros	**37%**
Top 10 Metros	**51%**

DOD	
Washington, DC	17%
San Antonio, TX	6%
Virginia Beach, VA	5%
San Diego, CA	4%
Colorado Springs, CO	3%
Top 5 Metros	**34%**
Top 10 Metros	**47%**

FAANG+M	
Seattle, WA	41%
San Francisco, CA	32%
New York City, NY	6%
Boston, MA	3%
Washington, DC	2%
Top 5 Metros	**84%**
Top 10 Metros	**92%**

Finance	
New York City, NY	14%
Dallas, TX	7%
Chicago, IL	6%
San Francisco, CA	5%
Washington, DC	5%
Top 5 Metros	**37%**
Top 10 Metros	**54%**

Management Consulting	
Washington, DC	12%
New York City, NY	11%
Chicago, IL	10%
San Francisco, CA	6%
Boston, MA	6%
Top 5 Metros	**45%**
Top 10 Metros	**65%**

Manufacturing	
Detroit, MI	13%
San Francisco, CA	8%
Atlanta, GA	6%
Austin, TX	4%
Dallas, TX	4%
Top 5 Metros	**36%**
Top 10 Metros	**51%**

Software	
San Francisco, CA	17%
New York City, NY	8%
Seattle, WA	5%
Boston, MA	5%
Washington, DC	5%
Top 5 Metros	**41%**
Top 10 Metros	**60%**

Other Industries	
San Francisco, CA	10%
New York City, NY	9%
Los Angeles, CA	5%
Chicago, IL	4%
Boston, MA	4%
Top 5 Metros	**32%**
Top 10 Metros	**50%**

All Industries	
San Francisco, CA	13%
New York City, NY	8%
Seattle, WA	7%
Washington, DC	5%
Boston, MA	4%
Top 5 Metros	**37%**
Top 10 Metros	**55%**

Source: CSET analysis of Revelio Labs data based on location data listed for unique positions.

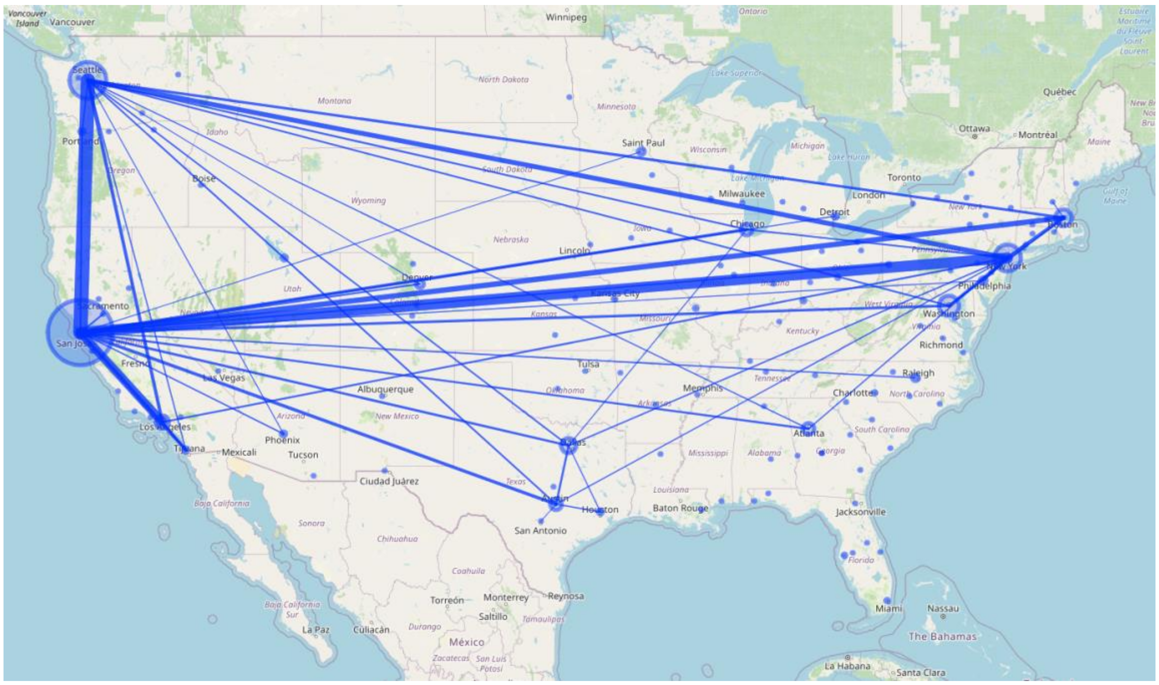
Similar to the sectoral cross-flow analysis, this disparity suggests the defense community's talent pool is concentrated in different hubs than the broader tech workforce. While this separation is not necessarily a problem in and of itself, it could mean that ideas, best practices, and technologies filter into the defense community more slowly.

To better understand geographic trends, we also visualized hubs of technical talent by industry sector along with movement between these hubs. For each figure, we display the 50 metro areas with the highest number of technical job positions in our dataset, scaled proportionate to their total tech positions, as well as the 50 largest connections between city-pairs based on the number of individuals who move cities to take a new job. The figures below display bi-directional flows of technical talent (i.e., the sum of all position moves from metro A to metro B, as well as from metro B to metro A, between 1998 and 2021). The bubble around each metro area represents the total number of technical positions within that hub for the given industrial sector.

Similar to Table 8, our visualizations demonstrate that for most industry sectors studied here, a few American cities stand out as reservoirs of technical talent. However, the central hubs for technical talent varies by industry sector, ranging from Silicon Valley and Seattle to New York City and Washington, D.C. The DIB, for example, is far more aligned with large military installations than with known Big Tech hubs on the west coast.

Figure 4 illustrates the relative distribution of technical talent who work in the software technology industry, including FAANG+M (Big Tech) firms. The distribution is similar to the data shown in Table 2, not surprising given that this sector employs more than one-third of all technical talent in the United States. Notably, San Francisco and Seattle stand out as major hubs, with a strong connection to New York City. (A separate map of only FAANG+M firms showing an even more dominant cross-flow between San Francisco and Seattle is in Appendix D.)

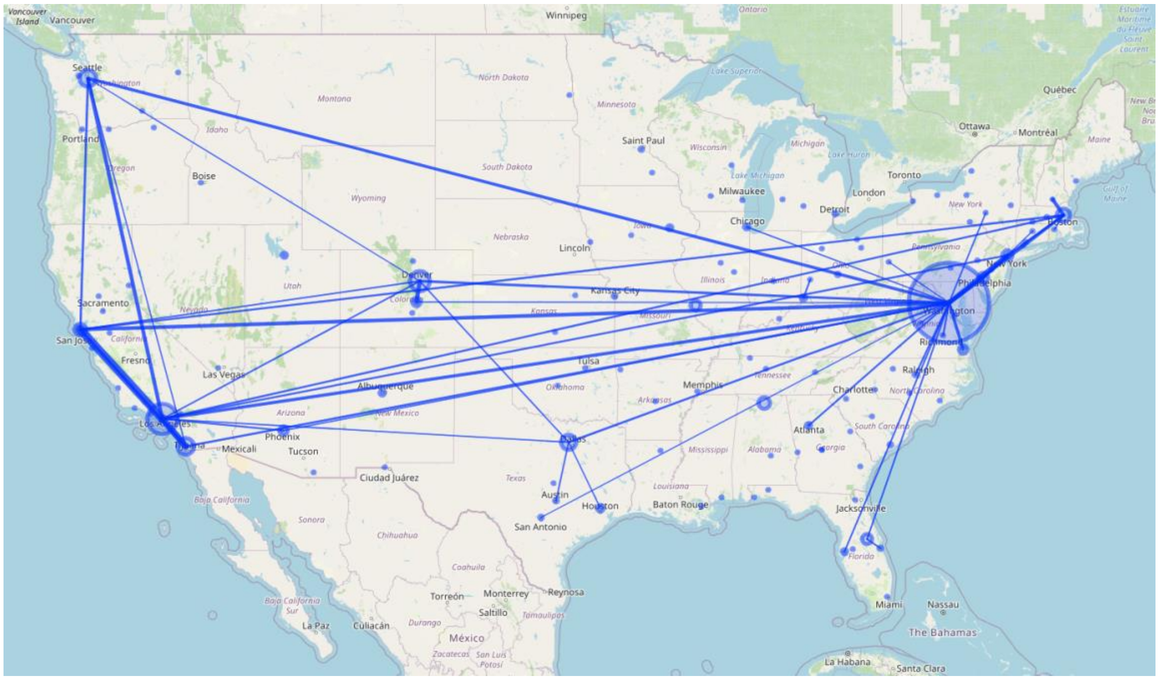
Figure 4. Geographic Flows of Technical Talent, Software Sector (Top 50 Metros)



Source: CSET analysis of Revelio Labs data.

In contrast, Figure 5 displays the relative distribution of technical talent employed by the DIB. Unlike the West Coast-centric map of the commercial software sector, the DIB map has a distinct East Coast bias clearly centered on Washington, D.C., with other hubs such as San Diego and Denver being well-known military hubs.

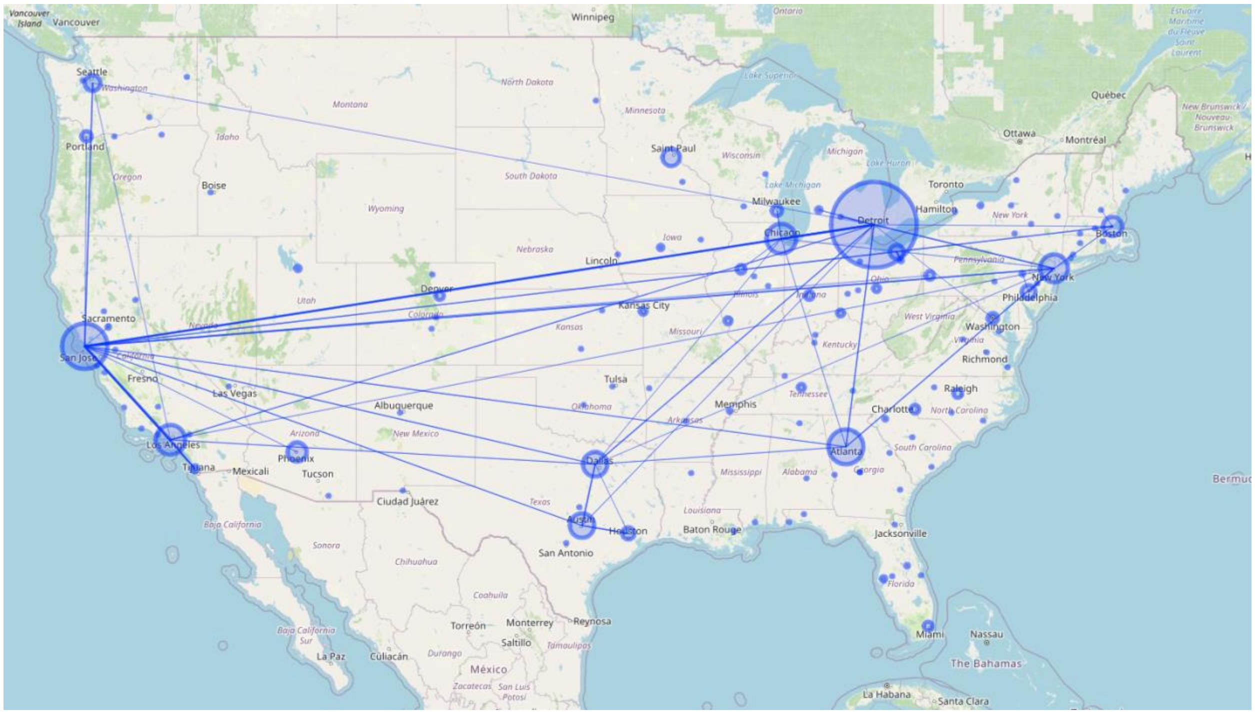
Figure 5. Geographic Flows of Technical Talent, DIB (Top 50 Metros)



Source: CSET analysis of Revelio Labs data.

Finally, Figure 6 shows the distribution of technical talent across the Manufacturing sector—a more traditional industry compared to the tech-centric software sector. While Detroit is the most important hub of technology talent for this industry sector (no surprise given its central role in automotive manufacturing), the sector has a significant presence in most of the other major American hubs for technical talent. Other industrial sectors such as Consumer Goods and Health demonstrate a similar pattern.

Figure 6. Geographic Flows of Technical Talent, Manufacturing Sector (Top 50 Metros)



Source: CSET analysis of Revelio Labs data.

Key Findings for the Defense Community

Our analysis generally supports the prevailing narrative about the distribution of technical talent in the United States, with a significant portion of positions concentrated in the so-called Big Tech companies and a relatively weak talent pipeline within the defense community. However, understanding the nuances of these trends is critical for defense leaders to strengthen their tech workforce and access new pools of talent. Specifically, our analysis offered three broad findings related to the defense community:

Finding 1: The defense community is not replacing or expanding its tech workforce at the same rate as other industry sectors.

The U.S. technical workforce has grown overall since the early 2000s, but the distribution of that workforce has changed significantly during that time. Most notably, the share of overall tech positions in the Big Tech companies (FAANG+M) more than quadrupled over the past two decades while the share of positions in the defense community (DOD and DIB) fell roughly 40 percent.[47] This does not necessarily mean that the overall number of tech workers in the defense community decreased during this time, but it does suggest the DOD and DIB have not been expanding their tech workforce at the same rate as other sectors. No other industry sector in our analysis saw its share of U.S. tech positions decline to the same degree over the last two decades. Additionally, the data suggests the overall outflow of technical talent from DOD has exceeded inflow to the department since the late 1990s. (This may result from several factors unique to the military, such as natural career attrition.)

It is worth noting that these trends are more pronounced in the DOD than the DIB, and as such, the defense community would be wise to view the DIB as a vehicle for accessing technical talent. The DIB's share of tech positions has plateaued at around 4 percent since the early 2010s, which suggests that defense contractors have established a relatively stable talent pipeline. The DIB also maintains an inflow-to-outflow rate that is in line with the other major industry sectors studied here, while over 75 percent of the DOD's net talent industry flows were outgoing.

Moreover, given that the disproportionately high share of technical talent leaving the DOD moves to the DIB, it is clear that there is a marketplace for technical talent with DOD expertise. Recognizing and leveraging the importance of the DIB could particularly be valuable regarding access to specialized technical talent such as those with AI and data engineering skills.

While not the focus of this report, it is worth noting that investing in companies such as Palantir, Anduril, and SpaceX could allow the DOD to expand its pool of technical experts. However, despite these notable examples, broader efforts to incorporate innovative startups into the defense industrial base have had limited success. This suggests the DOD would benefit from better understanding the current barriers related to the success of these investments, which we note is currently a topic of active study and discussion.[48]

Finding 2: The defense community remains relatively isolated from other sectors in terms of talent cross-flow and geographic hubs, which can slow technology adoption.

Our analysis found limited cross-flow of talent between the defense community and the commercial software sector, particularly the FAANG+M firms. Additionally, tech workers in both the DOD and DIB had longer average tenures than their counterparts in other industry sectors.

While low turnover is not a problem in and of itself, when combined with low sectoral cross-flow and net outflow of talent, it can hamper the defense community's ability to adopt and drive technological innovation. Employee turnover and industry cross-flow can both inject organizations with new ideas, skills, and techniques, which all contribute to innovation. This limited cross-flow could hinder the defense community's ability to adopt cutting-edge technologies and business practices developed in other commercial tech sectors, potentially leaving the military at a disadvantage against adversaries.[49] It also creates a second order effect where talent staying longer in the DOD could result in fewer opportunities for cross-pollination of innovative ideas.

This trend is potentially exacerbated by the relatively weak geographic overlap between the defense community and the commercial software industry. While the DOD and DIB have geographic hubs centered around Washington, D.C., the commercial software workforce is heavily concentrated in other metro areas, such as San Francisco, Seattle, New York City, and Boston. These differences in geographic concentration suggest there are fewer organic opportunities for innovation-enhancing, idea cross-pollination.

The relatively long tenures and low cross-flow of workers in the defense community suggest that "civil service as a lifelong career" remains a prevalent mindset within the national security workforce. On the civilian side, talent may come in and stay for a long time—a positive only if there are routine opportunities for professional development that refresh skills and garner exposure to the latest techniques. On the uniformed side, an "up or out" promotion culture rewards battlefield and operational command over technical expertise for institutional reasons, but as a result many technical junior officers are leaving service mid-career with limited attractive options to return. However, changing the current cultural mindset to one that promotes more permeability, even for civilian talent, will require dedicated effort.

Finding 3: The Department of Defense recruits a relatively small share of its tech workforce from top-ranked computer science schools, an imperfect but commonly used proxy for quality.

Only about one-fifth of tech workers within DOD hold degrees from top-ranked universities, compared to more than half of the workers at the FAANG+M firms. While university rankings are a highly imperfect proxy for actual skills, many in non-defense industry sectors view the prestige of an employee's degree as an indicator of their overall quality. Our data shows talent from ranked institutions, particularly top ten institutions, moves more often to these select firms, potentially limiting the defense community's ability to compete by at least one measure of quality.

Our analysis shows that not only are these firms taking a disproportionate share of the available technical talent, but they also preferentially recruit workers from the top-ranked institutions. We believe this is because the fiercest competition for technical talent is likely for so-called "exceptional" or highly qualified talent,[50] which is hard to perfectly identify but nevertheless in high demand.[51] While many workers are good, they are not "exceptional" in the economic sense.[52] For example, there is an idea among some in the tech community that, in software engineering, exceptional software engineers are at least ten times more productive compared to coworkers of average ability (see text box on pg. 27). This is evidenced by many of the largest technology companies incorporating this belief into their talent management practices.[53] Meanwhile, the DOD—and the federal government more broadly—have few ways to reward exceptional talent within existing pay scales and career paths. While DIB firms are not bound by pay scales, they must adhere to DOD rules and regulations that could limit their ability to compete for top talent in the same way as other firms.

To be sure, some technical talent in the defense community is “exceptional.” This talent could have come through military academies or routine enlistment. On the civilian side, exceptional talent may have chosen the DOD or DIB for professional and personal reasons outside of salary, such as mission, work-life balance, or burnout. But there will inevitably be a risk for this talent to leave the defense community for non-defense industry sectors, especially if attractive options to stay do not exist.

Potential Implications for the Technical Talent Labor Market

While not studied in depth here, our findings also provide some evidence of two potential broader economic implications. We note them here because, if true, they could present a potential national security concern.

First, the technical talent labor market may be further from a single market—more imperfect and segmented in terms of competitive access——than realized. As the demand for exceptional talent and market concentration both increase, firms with large market power have greater incentive and ability to hire exceptional tech talent at the expense of other industry sectors. Our findings give some validation to this, showing that technical talent has become increasingly concentrated in Big Tech and in the geographic hubs where they are headquartered. Once employed by one of these top-tier tech companies, the prestige associated with these employer brands likely perpetuates people remaining within this community.[54]

Second, access to technical talent may vary by sector and region in the United States, which suggests this could also be the case elsewhere. Our data suggests differences in how the defense community accesses and retains technical talent relative to other industry sectors. This could have implications for defense workforce policy, in that DOD should create policies specific to its talent posture and needs. For example, even as more technical workers are working remotely, and in spite of the recent wave of layoffs, it may well be that a few tech employers could continue to dominate access to technical talent regardless of where talent resides. Also, while not explored here, it is possible other countries face a similar reality. For example, although much discussion is on broader national terms, this could well be the case in China.[55]

Policy Recommendations

Taken together, our findings suggest the labor market for technical talent is highly dynamic but also highly concentrated. Although supply is increasing, it is still becoming harder for firms to effectively compete without a wage spiral.[56]

Talent planners in the defense community would benefit from ensuring talent recruitment and management approaches reflect today's technical talent labor market. We believe that while the current allocation of technical talent is "efficient" (in an economic sense), given past and current market dynamics it may be distorted.[57] We think this holds true in spite of recent layoffs in Big Tech, which hired aggressively during COVID and continues to employ a large share of U.S. technical talent.[58] While this paper is not about industrial organization or the economics of innovation and scale, we acknowledge that the concentration of talent seen in our data over the last decade is an important consideration that affects policy direction.[59]

Based on our findings and implications, we offer four recommendations for the DOD:[60]

Recommendation 1: Collaborate and partner as needed with the commercial software sector, promoting sectoral cross-over. The DOD should build targeted relationships with the private and nonprofit tech communities for technical talent, sharing and rotation agreements.[61] These partnerships should systematically emphasize permeability, so that there are consistent options across the entire defense community for talent to come and go as needed. It should include multiple types of arrangements, from gig assignments to short-term career pathways, part-time and full-time, along with any necessary modifications to recruitment and retention policies. For example, programs such as the Defense Ventures Program and the Air Force's Education With Industry are promising and should be expanded. More options to work with and for the DOD could also increase access to highly qualified technical talent who may not wish to join DOD long-term but still want to support the mission.

DOD partnerships and career pathways must also be designed to go both ways to get the best of both upskilling and talent access. This is because staying in one career for the long term is not realistic as a workforce planning strategy, nor does it guarantee the routine exchange of ideas and techniques with industry sectors on the leading edge. For example, the defense community could consider orienting "gig" opportunities for civilians to the DOD, enabled by existing applications such as GigEagle.[62] The U.S. Digital Corps, Defense Digital Service, and reserve components such as the Army's 75th Innovation Command also provide good models that could be expanded upon.

Recommendation 2: Invest in the human capital of DOD's existing talent pool. Given the DOD's more limited ability to effectively attract technical talent relative to other industry sectors, it should double down on investment in identifying, training, and leveraging the cadre of talent that the community already has, much of which is high quality and dedicated to the mission.[63] This includes investment in regular upskilling and training, to incentivize participation in skills-enhancing education and training and leverage and reward talent that demonstrates technical expertise.[64] Efforts should emphasize data, analytics, software, cyber, and AI-related skills, including technical product management.

For example, this could mean expanding the offerings of the Air Force's Digital University to all servicemembers and civilians, or providing a professional development stipend for them to take other technical skills courses. Critically, these skills must also be identifiable in the DOD community, as well as leveraged in assignments and rewarded through consideration for future assignments and promotions. This may include implementing specialized skill and experience identifiers, but it may also include addressing other separate but interrelated issues, such as modernizing data infrastructure, facilitating access to cloud storage, computing and other analytic tools, and building technical expertise into capability requirements. This is consistent with CSET's previous report on the state of DOD's AI workforce, which showed that the Department already has a well-abled cadre of talent with technical skills that are not being effectively identified and leveraged.[65] That report similarly proposed recommendations targeted at DOD investing in better using its technical talent.

Recommendation 3: Increase the defense community's integration into the broader technical workforce. Given the importance of the DIB as a vehicle to access technical talent, DOD should document and mitigate the legal, regulatory, and other barriers that limit DOD and DIB competitiveness for technical talent. For example, DOD should dedicate serious effort to bring more DOD data to an unclassified environment. This would create opportunities both to engage the vast pool of uncleared technical talent and to facilitate more opportunities for remote or hybrid work as part of a data, analytics, software, cyber, and AI talent recruitment and retention strategy. Additionally, this could include more ways for talent to work on unclassified projects, and offsite—a well-documented challenge in the ability for technical talent to work on defense problems.[66] Ideally, as another conduit to the tech community, the DIB and the commercial software sector would be more intentional in working together to create innovative pathways for DIB firms to access top talent, similar to the DOD.

Recommendation 4: Cultivate a future civil-service-minded tech workforce. It is in the DOD's self-interest to dedicate resources and, in conjunction with other government departments and agencies, to work to increase the overall U.S. supply of tech talent while encouraging more youth to pursue civil service. This includes advocating for and participating in discussions tied to higher education reforms that promote standardized and accredited competency-based education and credentialing alongside traditional college degrees. This also includes leading by example to increase diversity, equity, and inclusion in the technical workforce through greater use of hiring practices that legitimize alternative credentials. This could also elevate and prioritize the discovery of exceptional talent through less traditional market signals, leaving no talent behind.[67] Finally, while not discussed in detail here, it also includes creating a culture in which technical talent can thrive and want to stay.

Conclusion

Access to technical talent—and the novel ideas, expanded social networks, and increases in human capital that come with talent migration—is critical to U.S. innovation. This is especially true for the defense community, which must have sufficient access to cutting-edge technologies and the talent that designs, develops, and deploys them.

The conventional wisdom guiding today's policy discourse is one where the DOD and defense community writ large struggle to access the technical talent it needs. Instead, it is Big Tech firms—Facebook (Meta), Apple, Amazon, Netflix, Google (Alphabet), and Microsoft—that are best able to compete for this talent. Even the recent wave of tech-industry layoffs is unlikely to change the broader labor market dynamics. Still, little comprehensive data is available on the technical talent labor market, particularly with regard to the defense community. To address this gap, using data from Revelio Labs based on LinkedIn positions with start dates between 1998–2021, we analyzed the movement of technical talent in the United States across industry sectors and major metro areas over time.

Our analysis validates some of the conventional wisdom about the increasing market power of Big Tech firms as it relates to accessing technical talent. While we do not causally explain these findings and implications, our findings are also consistent with the very real potential that the DOD is operating in a distorted and segmented labor market for technical talent. Our analysis also revealed three major trends related to the defense community's tech workforce:

1. **The defense community is not replacing or expanding its tech workforce at the same rate as other industry sectors.**
2. **The defense community remains relatively isolated from other sectors in terms of talent cross-flow and geographic hubs, which can slow technology adoption.**
3. **The Department of Defense recruits a relatively small share of its tech workforce from top-ranked computer science schools, an imperfect but commonly used proxy for quality.**

While none of these trends are necessarily problems in and of themselves, when taken together they can result in an environment that is not adequately equipped to recruit and retain talent, drive innovation, and adopt emerging technologies across the enterprise. We propose four recommendations for how the defense community can begin addressing these challenges and better access technical talent:

1. **Collaborate and partner as needed with the commercial software sector, promoting sectoral cross-over and industry exchanges.**
2. **Invest in the human capital of the existing talent pool.**
3. **Investigate how to encourage the DOD and DIB to become more integrated with the larger U.S. technical workforce.**
4. **Cultivate a future civil-service-minded technical workforce.**

Consistent with previous CSET research, we believe the defense community has a sizable cadre of technical talent that must be appropriately identified and leveraged. Moreover, and as important, the defense community has a critical role in growing and diversifying the domestic pipelines for future technical talent. Embracing both realities will go a long way to not only ensuring the DOD's access to technical talent is sufficient, but to positioning the United States for future global workforce competitiveness.

Ultimately, our findings suggest the DOD's current strategies for accessing technical talent may not be appropriately targeted or reflect the reality of today's labor market dynamics. The recent layoffs across the tech industry may offer the defense community an opportunity to attract new cadres of talent and make inroads with a younger generation of technologists who are open to working in new sectors.[68] Without a shift in mindset, however, the national security community may continue to struggle to recruit and retain the necessary technical talent.

Appendix A: Defining Tech Talent

We identified technical talent using the "technical team" framework developed in prior CSET research.[69] Our analysis specifically focused on Technical Team 1 occupations, which includes highly technical roles and responsibilities associated with the design, development, and deployment of AI. The 18 occupations included in this team are listed in Table A1.

Table A1. Technical Team 1 Occupations

Technical Team 1 Occupations		
Computer and Information Systems Managers	Database Administrators	Mathematicians
Computer and Information Research Scientists	Database Architects	Operations Research Analysts
Computer Systems Analysts	Network and Computer Systems Administrators	Statisticians
Computer Programmers	Computer Network Architects	Data Scientists
Software Developers	Information Security Analysts	Mathematical Science Occupations, All Other
Software Quality Assurance Analysts and Testers	Computer Occupations, All Other	Computer Hardware Engineers

Source: CSET.

In order to conduct our analysis, we needed to map Revelio Labs' data to the CSET definition of Technical Team 1 occupations. To identify these technical job positions, we relied on the role_k1000 data element from Revelio Labs' dataset. They use an algorithm to populate this column by analyzing all the job position information available and assigning each position to one of 1,000 buckets that describe the largest groups of similar types of jobs in their dataset. Of these 1,000 buckets, 111 defined job categories that we considered to be a type of technical talent. These categories included roles such as Data Center Operator, IT Project Manager, and Software Engineer.

In some cases, roles included a mix of technical and nontechnical talent. For example, a Development Manager could be a software engineer managing a team of other software engineers (often referred to as software developers). However, in other contexts, a Development Manager might refer to an employee of a nonprofit who raises funds from donors. Similarly, the Researcher category includes many different kinds of researchers, some of whom focus on topics related to software and computer hardware and some who do not. For these ambiguous job groupings, we added a requirement that the individual holding the job must hold a technical degree. For three job categories, we filtered out job positions where the worker did not have a PhD in a relevant educational field. For 23 other categories, we required at least a bachelor's degree in a relevant field.

Table A2 provides the full list of included job categories and specifies which required a relevant educational background. Applying these restrictions resulted in a dataset with a total of 14,514,403 job positions held by 6,407,598 unique users.

Table A2. K1000 Roles Included in Technical Team 1

K1000 Role		
.NET Developer	Information Technology Project Manager	Sharepoint Developer
Advisory Software Engineer*	Infrastructure Analyst	Software Consultant*
Analyst Programmer	Infrastructure Architect	Software Designer
Analytics Specialist	Infrastructure Engineer	Software Developer
Android Developer	Integration Engineer*	Software Development Engineer in Test
Application Development Analyst	IT Analyst	Software Engineer
Application Development Associate	IT Architect	Software Engineer I
Cloud Architect	IT Engineer	Software Engineering

K1000 Role		
Computer Engineer	IT Operations	Software Project Manager
Cyber Security Specialist	IT Project Manager	Software Test Engineer
Data Analyst	IT Specialist	Software Tester
Data Analytics	Java Developer	Solutions Architect*
Data Architect	Linux System Administrator	Solutions Engineer*
Data Center Operator	Machine Learning Engineer	Statistician
Data Engineer	Network Analyst	Storage Engineer
Data Scientist	Network Architect	System Administrator
Database Administrator	Network Consulting Engineer	System Administrator
Database Analyst	Network Engineer	System Architect*
Database Developer	Network Engineering	System Developer*
Database Specialist	Network Operations	System Engineer*
DBA	Network Specialist	Systems Administrator
Developer	Network Support Engineer	Systems Analyst*
Development Engineer*	Network Technician	Systems Architect*
Development Manager*	Operations Analyst	Systems Engineer*
DevOps Engineer	Oracle Developer	Systems Engineering*
Digital Product Manager	Professor^	Systems Programmer*
Embedded Software Engineer	Programmer	Technical Architect*
ETL Developer	Programmer Analyst	Technical Lead*

K1000 Role		
Frontend Developer	R&D Engineer*	Technical Product Manager
Full Stack Developer	R&D Specialist*	Technical Project Manager
Hardware Engineer*	Research and Development Intern*	Technical Test Specialist
I.T. Analyst	Researcher^	Technology Lead*
Information Analyst	RPA Developer	Test Automation Engineer
Information Security	Salesforce Developer	UI Developer
Information Systems Specialist	Security Analyst*	Unix System Administrator
Scientist^	Security Architect	User Experience Researcher
SDE	Security Engineer	UX Designer

* = Technical degree requirement (bachelor's or higher in Computer Science, Computer Engineering, or Electrical Engineering)

^ = Technical PhD requirement (Computer Science, Computer Engineering, Electrical Engineering, Mathematics, or Statistics)

Appendix B: Defining Talent Flows

Geographic Talent Flows

This report builds upon previous CSET research by examining how technical talent flows between major tech hubs, and measuring the relative strength of these connections. Mapping this network offers insights about the relative importance and influence of the various technology hubs distributed throughout the country.

The dataset provided by Revelio Labs includes two fields specifying the location for each job position: location and country. Location is an optional text field filled in by users; no format is enforced or required. Country is derived by Revelio Labs based on the information entered into the location field. Because this report focuses on U.S. tech talent, our analysis only includes positions for which Revelio Labs identified the country as "United States."

We normalized the location data to map each position to a specific metropolitan area. We delineated U.S. metros using Core-based Statistical Areas (CBSAs), a set of geographic areas defined by the Office of Management and Budget and used by the U.S. Census Bureau. We then determined which localities (city/state pairs) were located in each CBSA, using data from the Department of Housing and Urban Development. Finally, in some cases we combined CBSAs that were in close proximity to each other. For example, San Jose, California, and San Francisco, California, were originally defined as separate CBSAs. However, for our purposes, these tech communities are closely tied to each other and an individual could easily leave a job in the San Jose CBSA and take a new job in the San Francisco CBSA without actually changing his or her physical residence. Consequently, analyzing these CBSAs separately would have distorted the findings of the report. Table B1 includes a full list of CBSA combinations.

We then used the Revelio Labs location data to map each position to a CBSA. We did so by parsing the location text to identify either city/state pairs, unique city names and references, or references to specific geographic locations ("the Pentagon", "Ft. Meade", etc.). Of the 14,514,401 technical positions in our dataset, we were able to map 13,227,944 (91.1 percent) to a U.S. metro area.

Table B1. CBSA Combinations

Combined Metro Area	Included CBSAs
Washington–Arlington–Alexandria, DC–VA–MD–WV	Washington–Arlington–Alexandria, DC–VA–MD–WV; Baltimore–Columbia–Towson, MD
Denver–Aurora–Lakewood	Denver–Aurora–Lakewood, CO; Boulder, CO
Detroit–Warren–Dearborn	Detroit–Warren–Dearborn, MI; Ann Arbor, MI
New York–Newark–Jersey City, NY–NJ–PA	New York–Newark–Jersey City, NY–NJ–PA; Bridgeport–Stamford–Norwalk, CT
Raleigh, NC	Raleigh, NC; Durham–Chapel Hill, NC
Salt Lake City, UT	Salt Lake City, UT; Heber, UT; Ogden–Clearfield, UT; Provo–Orem, UT
San Francisco–Oakland–Hayward, CA	San Francisco–Oakland–Hayward, CA; San Jose–Sunnyvale–Santa Clara, CA
Colorado Springs, CO	Colorado Springs, CO; Cañon City, CO

Industry Sector Talent Flows

In addition to examining the migration of technical talent between metro areas, we also explored the migration of technical talent between different industrial sectors. Each position in the Revelio Labs dataset included fields specifying the company and industry sector of the job. Revelio Labs used the industrial categories defined by LinkedIn's taxonomy to make these assignments; each position was assigned to the industry sector that its company was assigned to.

For our analysis, we grouped LinkedIn's industrial categories together thematically. For example, we grouped six LinkedIn industries (Insurance, Banking, Investment Management, Investment Banking, Capital Markets, and Venture Capital & Private Equity) into a single Finance industry category. Additionally, we created four custom categories for sectors of particular interest to this analysis. The FAANG+M category includes six major technology companies (Facebook/Meta, Apple, Amazon, Netflix, Microsoft, and Google/Alphabet) and is frequently used as a shorthand for discussing America's technology giants. The Defense Industrial Base category (DIB) includes two of LinkedIn's defined categories (Aerospace & Aviation plus Defense & Space) as well as the 50 U.S. defense contractors that appeared in the 2021 *DefenseNews* Top 100.[70] Table B2 includes a complete list of Revelio Labs industry groupings.

Table B2. LinkedIn Industry Groupings

Mapped Industry Sector	Definition
DIB	**LinkedIn Industries:** Defense & Space; Aviation & Aerospace **Custom Grouping:** 50 U.S. Companies in 2021 *DefenseNews* Top 100
DOD	**Custom Grouping:** Manual assignment of U.S. Department of Defense components
FAANG+M	**Custom Grouping:** Facebook/Meta, Apple, Amazon, Netflix, Google/Alphabet, Microsoft
Finance	**LinkedIn Industries:** Insurance; Banking; Investment Management; Investment Banking; Capital Markets; Venture Capital & Private Equity
Management Consulting	**LinkedIn Industries:** Management Consulting
Manufacturing	**LinkedIn Industries:** Automotive; Electrical/Electronic Manufacturing; Machinery; Chemicals; Industrial Automation; Building Materials; Paper & Forest Products; Plastics; Textiles; Glass, Ceramics & Concrete; Railroad Manufacture; Shipbuilding

Software	**LinkedIn Industries:** Information Technology and Services; Computer Software; Internet; Computer Games; Computer & Network Security

Finally, the DOD category includes all components of the U.S. Department of Defense; these organizations were mapped inconsistently to LinkedIn industries in the original source data. Table B3 lists the complete mapping for these categories.

Table B3. Department of Defense Components Included in DOD Industry Sector

DOD Component		
Aberdeen Proving Ground	Tactical Air Command	United States National Geospatial-Intelligence Agency
Air Combat Command	The Bureau of Naval Personnel	United States National Guard Bureau
Air Education & Training Command	The Defense Commissary Agency	United States National Reconnaissance Office
Air Force Space Command	The Military Postal Service Agency	United States National Security Agency
Air National Guard	The Portsmouth Naval Shipyard	United States Naval Air Systems Command
Arkansas National Guard	The United States Army (District of Columbia)	United States Naval Sea Systems Command
Army National Guard	The United States Army Judge Advocate General’s Corps	United States Navy (District of Columbia)

DOD Component		
Arnold Engineering Development Center	U.S. Army Corps of Engineers	United States Navy Reserve
Defense Contract Audit Agency	U.S. Army Medical Department	United States Northern Command
Defense For International Security Affairs	U.S. Army Medical Research Institute for Infectious Diseases	United States Office of Naval Research
Defense Legal Services Agency	U.S. Army Research Laboratory	United States Office of the Director of National Intelligence
Defense Manpower Data Center	U.S. Army Sustainment Command	United States Pacific Air Forces
Defense Media Activity	U.S. Army War College	United States Pacific Command
Defense Nuclear Facilities Safety Board	United States Air Force Academy	United States Pacific Fleet
Defense Security Service	United States Army Forces Command	United States Patrick Space Force Base
Defense Supply Center Columbus	United States Army Fort Bragg	United States Pentagon Force Protection Agency
Defense Technical Information Center	United States Army Intelligence & Security Command	United States Seymour Johnson Air Force Base
Defense Threat Reduction Agency	United States Army Reserve	United States Southern Command

DOD Component		
Department of Defense Education Activity	United States Army Training & Doctrine Command	United States Strategic Command
Department of Defense Military Health System	United States Central Command	U.S. Air Force
Florida Air National Guard	United States Defense Intelligence Agency	U.S. Air Force Intelligence Surveillance & Reconnaissance Agency
Fort Drum	United States Defense Security Cooperation Agency	U.S. Army Corps of Engineers, Mobile District (Alabama)
Fort Irwin National Training Center	United States Edwards Air Force Base (California)	U.S. Army Corps of Engineers, Omaha District (Nebraska)
Fort Monmouth	United States Eglin Air Force Base	U.S. Coast Guard
Fort Monroe	United States European Command	U.S. Cyber Command
Fort Sill	United States Fort Hood Army Base	U.S. Defense Advanced Research Projects Agency
Joint Forces Staff College	United States Hanscom Air Force Base	U.S. Defense Contract Management Agency
Joint Improvised Explosive Device Defeat Organization	United States Hickam Air Force Base	U.S. Defense Finance & Accounting Service
Los Angeles Air Force Base	United States Holloman Air Force Base	U.S. Defense Information Systems Agency

DOD Component		
Naval Air Weapons Station	United States Joint Chiefs of Staff	U.S. Defense Logistics Agency
Naval Criminal Investigative Service	United States Joint Forces Command	U.S. Department of Defense (District of Columbia)
Naval Reserve Officer Training Corps	United States Keesler Air Force Base	U.S. Department of the Air Force
Navy Exchange Service Command	United States Langley Air Force Base	U.S. Military Academy
New York Army National Guard	United States Marine Corps	U.S. Missile Defense Agency
North American Aerospace Defense Command	United States Marine Corps Air Station Miramar	U.S. Special Operations Command
U.S. Transportation Command		

Data Universe

Our analyses are based on a subset of LinkedIn users working in technical positions in the United States. Tables B4 and B5 show the different variables used to isolate this group.

Overall, the Revelio Labs dataset contained approximately 1.2 billion unique positions and roughly 716 million unique users. Of those, 320 million positions and 168 million users were located in the United States. Using the methodology described in Appendix A, we identified about 14.5 million of those U.S. positions as “technical roles.” These positions were distributed across approximately 6.4 million unique users. This sample of U.S. technical positions and users is the basis of our analysis.

Of the roughly 14.5 million U.S.-based technical positions in our sample, approximately 12.6 million positions (87 percent) had a start date that fell within our selected time period (1998 to 2021). Of these, we were able to map about 12.0 million (95 percent) to an industry sector and 11.5 million (91 percent) to a U.S. metro area. Of the 6.4 million unique users that held U.S.-based technical positions, approximately 4.3 million (66 percent) included information on their postsecondary education (college attended and degree earned).

Table B4. Data Sample Sizes for Positions Analyzed

Positions (Revelio Labs)	Included	Excluded	Missing
All Positions	1,168,283,351	n/a	n/a
Country = United States	320,103,810	759,933,409	88,246,132
U.S. Position = Technical	**14,514,401**	304,552,561	1,036,848
Valid Start Date (1998–2021)	**12,647,149**	607,048	1,260,204
Valid Start Date + Industry	**12,047,462**	n/a	599,687
Valid Start Date + Metro Area	**11,516,638**	690,895	439,616
Valid Start Date + Industry + Metro Area	**11,040,562**	n/a	n/a

Table B5. Data Sample Sizes Users Analyzed

Unique Users (Revelio Labs)	Included	Excluded	Missing
All Users	716,396,864	n/a	n/a
Country = United States	168,513,125	534,055,642	13,828,097
U.S. Position = Technical	**6,407,598**	162,105,527	n/a
Unique Users (U.S. Technical)	**Included**	**Excluded**	**Missing**
Education	**4,250,645**	730,857	1,426,096

Source: CSET tabulations based on Revelio Labs data.

Appendix C: Data Limitations

While the dataset we relied upon for this report is extensive and detailed, it has some limitations.

First, some of the data fields—especially the location field—were manually entered by the individual users without any enforced standardization or normalization. Consequently, the data can in some cases be messy or ambiguous. For example, users sometimes entered only the name of the U.S. state their job position was located in and omitted the city or any other information that might allow us to match the information with a specific metro area (i.e., New York or Georgia).

Second, in some cases, data elements in the dataset were generated algorithmically. For example, Revelio Labs grouped the universe of job positions into 1,000 major groupings of similar types of jobs. However, in some cases, this could result in the co-mingling between relevant data and non-relevant data for our purposes. For example, many different kinds of companies and functions need to perform quality assurance on their final products and output, and the individuals responsible for performing these quality checks often have the job title "QA Engineer". However, this category does not distinguish between roles relevant to the purpose of our paper (technical talent for computer software or hardware) and roles that focus on other kinds of engineering.

Finally, we have to account for the possibility of biases in our dataset. Revelio Labs' dataset is primarily derived from user-entered data on LinkedIn. While this data is among the largest and most robust datasets describing the American workforce, the nature of the dataset might have biases. Some demographic categories of workers might be over- and under-represented in this kind of data (based on criteria such as age, employment category, access to broadband internet, or other potential biasing factors).

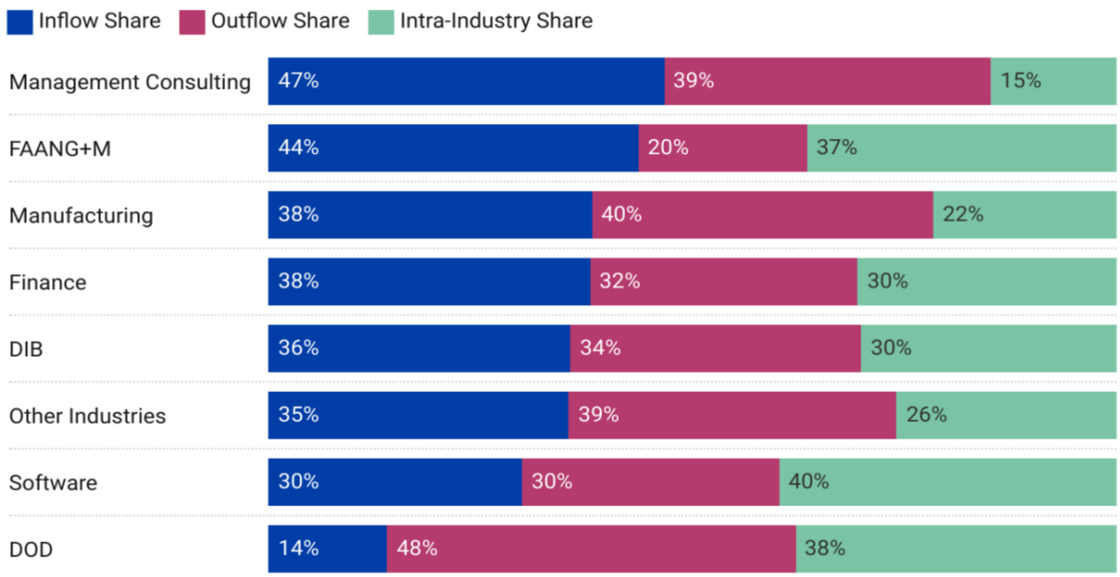
One way to potentially identify biases in the dataset is to explore whether we observe systematic skews in data variables that should be uncorrelated. For example, we compared whether the amount of experience for employees (measured in years) varied between the set of job positions whose industrial sector could be determined and job positions that could not be definitively assigned to an industry sector. We checked four relationships in total: whether the ability to identify a job's metro area affected the distribution of jobs across industry sectors, whether the ability to identify a job's metro area affected the distribution of employee experience levels, whether the ability to identify a job's industry sector affected the distribution of jobs across metro areas, and whether the ability to identify a job's industry sector affected the distribution of employee experience levels. We did not find substantial differences for any of these data validation checks. The biggest correlation was that a job's metro area was much more likely to be missing when the job's industry sector was also missing (and vice versa). Additionally, information about jobs for less experienced workers was more likely to have missing values.

Overall, these data validation checks increase our confidence that the data is not biased in a way that would skew our analysis or findings. At the same time, we have to allow for the possibility that our data remains biased in ways that may not be detectable by analyzing the data contained within the dataset.

Appendix D: Supplemental Charts

Figure D1 shows the share of position moves for each industry sector. "Inflow" represents workers entering the sector, "outflow" represents workers leaving the sector, and "intra-industry" represents workers taking new positions in the same sector.

Figure D1. Share of Industry Moves by Type, 1998–2021



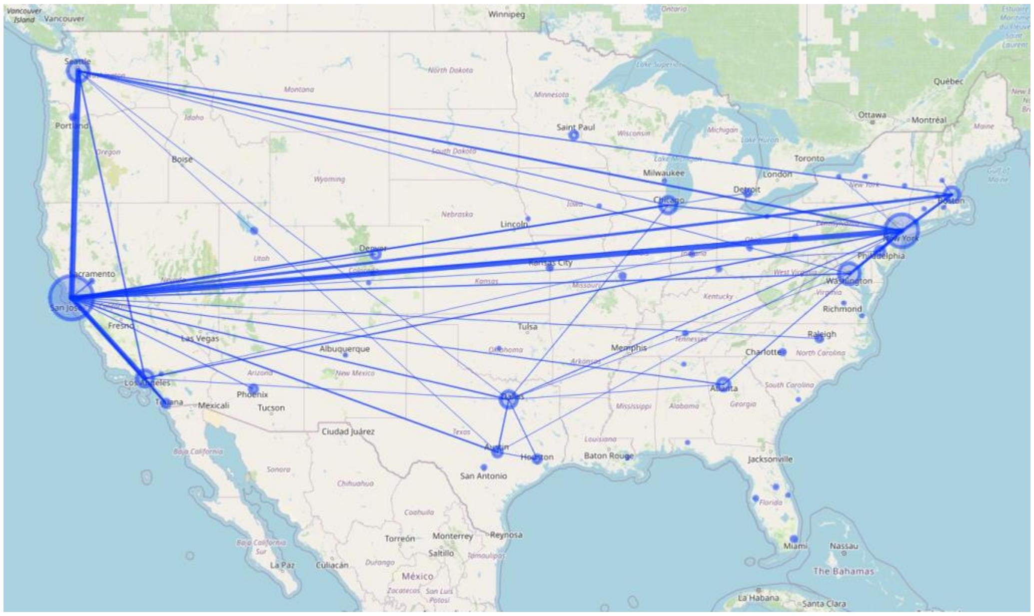
Note: "Intra-Industry" moves are those in which workers moved jobs within the same industry. Rows may not sum to precisely 100 percent due to rounding.

Source: CSET analysis of Revelio Labs data.

Figure D2 illustrates the relative distribution of technical talent across all industry sectors. Figures D3 and D4 show the relative distribution of technical talent working in the FAANG+M firms (Big Tech) and DOD respectively.

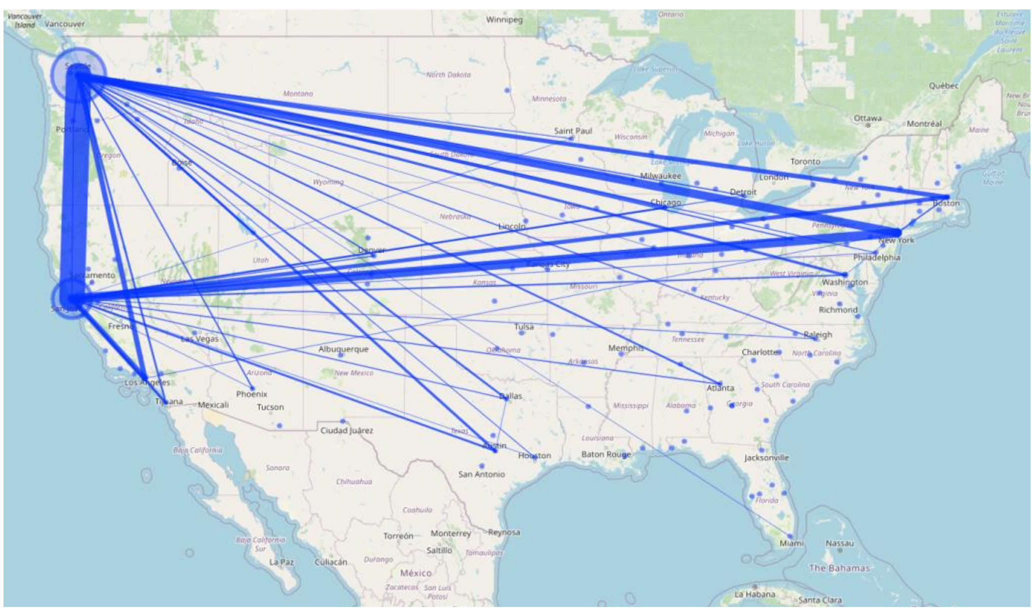
For each figure, we display the 50 metro areas with the highest number of technical job positions in our dataset, scaled proportionate to their total tech positions, as well as the 50 largest connections between city-pairs based on the number of individuals who move cities to take a new job. The figures below display bidirectional flows of technical talent (i.e., the sum of all position moves from metro A to metro B, as well as from metro B to metro A, between 1998 and 2021). The bubble around each metro area represents the total number of technical positions within that hub for the given industrial sector.

Figure D2. Geographic Flows of Technical Talent, All Sectors (Top 50 Metros)



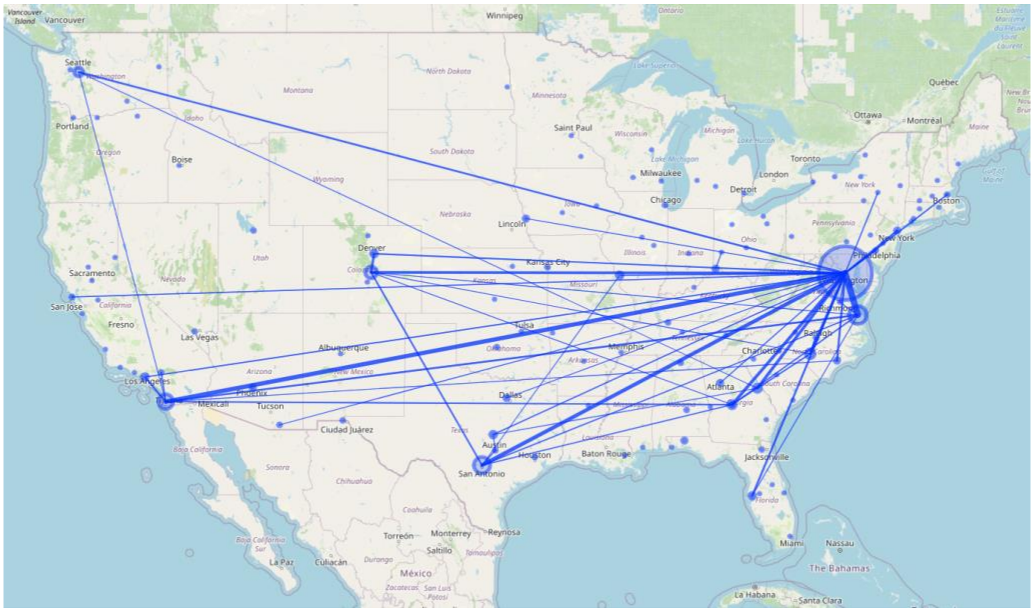
Source: CSET analysis of Revelio Labs data.

Figure D3. Geographic Flows of Technical Talent, FAANG+M Firms (Top 50 Metros)



Source: CSET analysis of Revelio Labs data.

Figure D4. Geographic Flows of Technical Talent, DOD (Top 50 Metros)



Note: This is essentially a map of Permanent Change of Station (PCS) moves for the U.S. military.

Source: CSET analysis of Revelio Labs data.

Authors

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Endnotes

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[21] Defined from a review of industry codes for high relevance within the Information and Professional Services sectors, as categorized in the North American Industrial Classification System (NAICS). For this analysis we define "key tech sectors" as software publishing, data hosting and processing, and computer systems design.

[22] We include the federal government in this table due to limited data availability for the Department of Defense specifically.

[23] U.S. Bureau of Labor Statistics, "American Time Use Survey Summary," *U.S. Department of Labor*, June 23, 2022, https://www.bls.gov/news.release/atus.nr0.htm. This has been enabled by advances in technology, such as cloud computing, integrated software platforms, communication and collaboration applications.

[24] AnnElizabeth Konkel and Nick Bunker, "July 2022 US Labor Market Update: Job Postings Are Sliding in Tech Hubs," *Indeed.com*, July 28, 2022, https://www.hiringlab.org/2022/07/28/july-2022-us-labor-market-update/.

[25] For example, see Jennifer Elias, "Google tells employees in Bay Area and other U.S. locations to return to offices in April," CNBC, March 2022: https://www.cnbc.com/2022/03/02/google-tells-employees-to-return-to-offices-in-april.html.

[26] Chris Morris, "Meta just gave thousands of employees poor performance reviews that could clear the way for more layoffs during its 'Year of Efficiency'," *Fortune*, February 17, 2023, https://fortune.com/2023/02/17/meta-employee-performance-reviews-layoffs/; Vishwam Sankaran, "Google is preparing to layoff 10,000 'poor performing' employees, report says," *The Independent*, November 23, 2022, https://www.independent.co.uk/tech/google-layoffs-poor-performing-employees-b2231056.html.

[27] Steve Lohr, "How Software is Stifling Competition and Slowing Innovation," *The New York Times*, July 21, 2022, https://www.nytimes.com/2022/07/21/business/software-james-bessen-book.html.

[28] While occupation codes are available as a field, they could not be reliably mapped to our occupations of interest.

[29] The FAANG+M category includes Facebook (Meta), Apple, Amazon, Netflix, Google (Alphabet), and Microsoft. The DOD category includes all components of the U.S. Department of Defense. The DIB category includes the 50 U.S. defense contractors that appeared in the 2021 *DefenseNews* Top 100, as well as all the other firms included in the "Aerospace & Aviation" and "Defense & Space" LinkedIn industry categories. Our DIB definition notably excludes many of the NSIN companies; given there is no

clear definition of the NSIN, we were unable to systematically determine which "non-traditional" vendors to include and exclude. See Appendix B for more details.

[30] Collectively, this includes 336 domestic and international universities. For more, see "2021 Global Ranking of Academic Subjects: Computer Science & Engineering," *Shanghai Ranking*, accessed May 2022, https://www.shanghairanking.com/rankings/gras/2021/RS0210; "QS World University Rankings by Subject 2022: Computer Science and Information Systems," QS Quacquarelli Symonds, accessed May 2022, https://www.topuniversities.com/university-rankings/university-subject-rankings/2022/computer-science-information-systems.

[31] All 10 schools appear in both the ARWU and QS top 500, and are generally considered to be an "elite" subset of those ranked institutions. For more, see "Best Computer Science Schools," *U.S. News & World Report*, accessed May 2022, https://www.usnews.com/best-graduate-schools/top-science-schools/computer-science-rankings?_sort=rank-asc.

[32] These figures are generally in line with the distribution of the broader technical workforce during each time period. Table 4 displays the number of technical positions in each industry with start dates during each time interval, which is different from the number of technical positions and unique workers in each industry at a single point in time. However, as a validation of these trends we also looked at both measures over time and found both measurements generally reflected the same trends in the talent distribution across industries and within industries over time.

[33] Many of the positions in our dataset were likely added retroactively as users back-filled their job history.

[34] The share of technical workers employed in finance was approximately 11 percent in both the Revelio and BLS datasets. The share employed in manufacturing was about 7 percent in the BLS data and 8 percent in the Revelio data. This Revelio figure includes both the "Manufacturing" category, as well as the DIB, which is heavily manufacturing focused.

[35] We note this analysis is somewhat limited by the data. Workers are counted as "entering" or "exiting" an industry sector when they move from a position in one sector to another. Workers who begin their careers in a particular industry sector are not counted as inflow for that sector as they had no previous position. Similarly, workers who end their careers in a particular industry sector are not counted as outflow. It is possible this methodology could also disproportionately undercount DOD inflow—given the comparatively sensitive nature of their work, DOD employees may potentially refrain from posting their positions on LinkedIn until after they have left the department. In such cases, workers would be recorded under "outflow" but not "inflow."

[36] Partnership for Public Service, "Who is quitting and retiring: Important fiscal 2021 trends in the federal government," accessed May 24, 2023: https://ourpublicservice.org/fed-figures/attrition/.

[37] This trend is further highlighted by the net inflow vs. outflow figures in Figure 2.

[38] Examples of academic research relying on this method include "Higher education, high-impact research, and world university rankings: a case of India and comparison with China", K.S. Reddy.

[39] Diana Gehlhaus and Luke Koslosky, "Training Tomorrow's AI Workforce: The Latent Potential of Community and Technical Colleges," Center for Security and Emerging Technology (CSET), April 2022.

[40] Originated from a study by Sackman, Erikson, and Grant in 1968; numerous additional studies over the years found similar results including Curtis 1981, Mills 1983, DeMarco and Lister 1985, and Boehm et al. 2000.

[41] Reed Hastings, "Netflix CEO on paying sky-high salaries: 'The best are easily 10 times better than average'," *CNBC*, September 8, 2020, https://www.cnbc.com/2020/09/08/netflix-ceo-reed-hastings-on-high-salaries-the-best-are-easily-10x-better-than-average.html.

[42] For more, see "Leadership Principles," *Amazon*, accessed December 2022: https://www.amazon.jobs/en/principles.

[43] We use the top 10 universities on the *U.S. News & World Report* list since it is one of the best known and most widely referenced rankings of computer science universities. While these are not the only universities that are priorities for software recruiters, we do not have access to the internal corporate documents that would allow us to further distinguish the relative desirability of graduates from the overall pool of global universities, colleges, and other educational institutions.

[44] Collectively, this includes 326 domestic and international universities. All the schools in the *U.S. News & World Report* top 10 also appear on both lists. For more, see "2021 Global Ranking of Academic Subjects: Computer Science & Engineering," *Shanghai Ranking*, accessed May 2022, https://www.shanghairanking.com/rankings/gras/2021/RS0210; "QS World University Rankings by Subject 2022: Computer Science and Information Systems," QS Quacquarelli Symonds, accessed May 2022, https://www.topuniversities.com/university-rankings/university-subject-rankings/2022/computer-science-information-systems.

[45] The military academies may be disadvantaged in some rankings of global universities because they do not offer graduate programs and place less emphasis on traditional academic research. The methodology for the ARWU, for instance, is based heavily on the quality and quantity of faculty research output, which tends to favor large research universities that excel in STEM fields. Similarly, because the military academies offer only undergraduate degrees, they would not appear in the *U.S. News* list of top computer science graduate programs. Finally, only 3 percent of technical staff in the DOD graduated from a military academy (and fewer than 0.5 percent of staff in any other industry graduated from a military academy), so even if military academies were considered to be "Ranked" schools, DOD would still have the lowest percentage of employees with degrees from "Ranked" universities.

[46] Gehlhaus and Rahkovsky, "U.S. AI Workforce: Labor Market Dynamics."

[47] FAANG+M grew its share of tech positions from 1.9 percent in 2002–2005 to 8.2 percent in 2018–2021. The combined DOD and DIB share of the tech workforce fell from 9 percent in 2002–2005 to 5.3 percent in 2018–2021.

[48] Flagg and Corrigan, "Ending Innovation Tourism."

[49] Interim Panel Report (Special Competitiveness Studies Project, October 2022), p. 28, https://www.scsp.ai/wp-content/uploads/2022/10/Defense-Panel-IPR-Final.pdf.

[50] While most employers believe they need this talent to compete, it is a very small segment of the workforce. That gives these workers incredible bargaining power, and—because they are interspersed among all technical talent—this bargaining power has extended to all technical talent generally.

[51] Diana Gehlhaus, Luke Koslosky, Kayla Goode, and Claire Perkins, "U.S. AI Workforce: Policy Recommendations" (Center for Security and Emerging Technology, October 2021).

[52] Here, "exceptional" is defined by productivity. That said, we believe good talent is critical to the success of any company and that for most companies exceptional talent as traditionally defined is not essential.

[53] For example, as Netflix explains in their culture guide, "Sustained 'B' performance … gets a severance package with respect," while Amazon insists that its managers should "raise the performance bar with every hire and promotion." For more, see "Leadership Principles," *Amazon*, accessed December 2022: https://www.amazon.jobs/en/principles.

[54] In part this was also likely enabled by the persistently low interest rates as set by the Federal Reserve. However, we acknowledge access to capital may become far more limited now, given rising interest rates and the current market downturn. This would potentially put firms in this tier only due to their high market capitalization at risk of moving to the "everyone else" tier.

[55] Although we also acknowledge China's civil-military fusion is designed to address exactly this concern. For more, see "Personnel of the People's Liberation Army," *U.S.–China Economic and Security Review Commission,* November 3, 2022, https://www.uscc.gov/research/personnel-peoples-liberation-army.

[56] Suman Bhattacharyya, "Tech Wage Inflation Puts Pressure on Companies," *The Wall Street Journal*, April 21, 2022: https://www.wsj.com/articles/tech-wage-inflation-puts-pressure-on-companies-11650533400?mod=article_inline.

[57] What may have been optimal for an individual company may have been suboptimal for the U.S. economy as a whole, effectively limiting competition to talent by creating artificially high barriers to entry. While this by itself is not offensive to economists, if the degree of inequality becomes extreme then a market intervention is warranted to create a more sustainable optimum.

[58] Noting also these trends are likely temporary due to economic headwinds unless there is a legal or regulatory intervention. For more, see Serah Lewis, "Big tech is bleeding thousands of jobs — but here's why the economy is going to 'very easily absorb' the layoffs in the sector," *Yahoo Finance*, November 19, 2022, https://finance.yahoo.com/news/big-tech-bleeding-thousands-jobs-150000296.html.

[59] Noting as well that historically uninterrupted low interest rates from the Fed's monetary policy also likely played a role in raising corporate market capitalizations and market power of select firms.

[60] We note a potential fifth option, leveling the competitive playing field through industrial policy, but the validity of engaging in such an action is a subject of intense research and debate outside the scope of this report.

[61] This is similar to the intention of the newly formed U.S. Digital Corps.

[62] Defense Innovation Unit, "Transforming DoD's Access to Talent," April 2022: https://www.diu.mil/latest/gigeagle-agile-talent-development-for-the-dod.

[63] Gehlhaus et al., "The DOD's Hidden Artificial Intelligence Workforce."

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[64] Stephanie Possehl, "Test and Evaluation—The Change is Here Today," *Defense Acquisition University*, February 1, 2022, https://www.dau.edu/library/defense-atl/blog/Test-and-Evaluation-change-today.

[65] Ibid.

[66] Mark Pomerleau, "Officials hope software factory for Air Force cyber operations squadron could be a retention and recruiting boon," *DefenseScoop*, September 19, 2022, https://defensescoop.com/2022/09/19/officials-hope-software-factory-for-air-force-cyber-operations-squadron-could-be-a-retention-and-recruiting-boon/.

[67] Diana Gehlhaus and Luke Koslosky, "Training Tomorrow's AI Workforce" (Center for Security and Emerging Technology, April 2022), https://cset.georgetown.edu/publication/training-tomorrows-ai-workforce/.

[68] Sam Sabin, "Exclusive: New poll finds tech workers considering defense work amid layoffs," *Axios*, March 17, 2023, https://www.axios.com/2023/03/17/tech-workers-military-defense-work-poll; Steve Lohr and Tripp Mickle, "As Silicon Valley Retrenches, a Tech Talent Shift Accelerates," *The New York Times*, December 29, 2023, https://www.nytimes.com/2022/12/29/business/silicon-valley-tech-talent-mainstream-industries.html.

[69] Diana Gehlhaus and Santiago Mutis, "The U.S. AI Workforce: Understanding the Supply of AI Talent" (Center for Security and Emerging Technology, January 2021), https://cset.georgetown.edu/wp-content/uploads/US-AI-Workforce_Brief-2.pdf#page=7.

[70] The *DefenseNews* Top 100 is an annual list of the world's top defense companies as defined by defense revenue. For more, see https://people.defensenews.com/top-100/.