Skills and Opportunity Pathways

Building an Inclusive Workforce for the Future

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July 2019

BROOKINGS

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Brookings Institution

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Executive Summary

Artificial intelligence and emerging technologies have enabled automation to scale and pose legitimate workforce threats. However, these innovations are creating new jobs and recreating old ones that together shape the building blocks of a future workforce. This dynamic opportunity engine is driven in large part by a fast expanding innovation ecosystem that combines a bevy of thriving, scaling, and nascent startups and their emerging workforce needs.

As the geography of innovation continues to evolve, the signals emerging from innovation clusters around the country provide crucial opportunity signals that policymakers should harness rather than ignore. Intriguing horizon workforce opportunities, for example, are embedded within this dynamic tapestry of startups and job creation. However, deliberate policies are required to ensure that underrepresented groups are fully included.

The U.S. must consider what innovation and new jobs mean for marginalized groups as innovation changes employers' demands for workforce talent and shapes the geography where new opportunities are most likely to emerge.

This report presents a framework that engages education policymakers and workforce planners in innovative ways. It assesses the scale and breadth of emerging trends across local job markets and intersects these data with regional innovation hubs to enhance the capacity of policymakers to design data-driven policies tailored to the strengths of individual ecosystems.

Highlights

NEW INNOVATION CITIES

New innovation cities are making a grand entrance on the innovation hub scene and offer promising opportunities for startup pipelines and new job creation.

SKILL COMBINATIONS AND TRANSFERABILITY

Innovation jobs and the skills required of an innovation workforce will be markedly different from those of the past. Employers are in the market for a combination of foundational STEM and tech-specific skills along with non-STEM skills, the portability of which offers workers opportunities to enrich their skill portfolios without starting over.

NEW POLICY LENSES

Increasing visibility into skill-portability opens new policy lenses for identifying skill-based entry points and meaningful pathway progressions to quality jobs.

TARGETED INTERVENTIONS

Solving the STEM pipeline problem requires a multi-pronged approach to level the playing field, including shifting from generic STEM policies toward targeted interventions.

Introduction

Artificial intelligence and other emerging technologies that have enabled automation to scale—which pose legitimate workforce threats—are simultaneously creating and recreating jobs that are the future of work.

An honest conversation about the future of work includes the power of automation to replace humans and create jobs, yet job creation—a crucial chapter in the automation story is often discounted. Artificial intelligence and other emerging technologies that have enabled automation to scale—which pose legitimate workforce threats—are simultaneously creating and recreating jobs that are the future of work. Despite this potential, the excessive emphasis on job destruction continues among policymakers to obscure the job-creation process unfolding across many cities, and perhaps to the detriment of progress. Devoting inadequate thought leadership and resources to understanding innovation-driven job creation will surely create missed opportunities for policymakers and the communities that they represent.

Amid the stoked fears of automation, discernible signals of the future are emerging and provide good reason to carefully analyze shifting tides. Fortunately, some experts are starting to see what's on the horizon: young, innovative firms diffusing advanced technology across the U.S. and fertilizing new industries in their wake. Emerging firms are aggressively adopting leading technologies and deploying them in diverse and unanticipated applications. Tracing the data footprints of these firms provides evidence of novel business models, new micro-industries, and emerging demand for the skills of the future.

This report presents a framework that offers worthwhile insights into the contours of the burgeoning job market, addressing three questions: How can policymakers anticipate and plan for employment demand as technology-enabled growth increases? What do the changes in employers' needs mean for the inclusion of historically underrepresented groups in the transforming workforce? And, how do policymakers actively close equity gaps for underrepresented minorities?

The analysis begins by tracing inconspicuous technology undercurrents to identify the geography and topology of innovation. Next, we examine the diverse skill demands of employers embedded in job-postings data to understand their emerging workforce needs. Finally, we review the gaps between employers' skill demand and worker skillsets to identify occupations that represent promising inclusion points for underrepresented groups.

The data reveal a landscape of innovation that is impressively diverse and vibrant. Intriguing horizon workforce opportunities are embedded within this dynamic tapestry. However, deliberate public policies and programs are required to ensure that underrepresented groups are fully included. This research also demonstrates that having the right skills is the currency of the future workforce. Tangible skills unlock opportunities for workers to access highly mobile pathways across a network of occupations as opposed to discrete jobs. We conclude that employers are keenly interested in a three-dimensional skill portfolio and workers endowed with high-quality STEM and tech-specific skills are rewarded with income premiums. Not surprising, Black, Hispanic, and Native American individuals are acutely absent from strategic opportunity occupations that offer high-quality wages and employment longevity. Creating access to these opportunity pipelines requires policy attention that links inclusion to targeted changes in the K-14 environment where underrepresented populations live, work, and go to school.

Landscaping Innovation

The geography of innovation is shifting, and the emergence of startup clusters is a prime signal of opportunity that should not be ignored, especially in places with shrinking options.

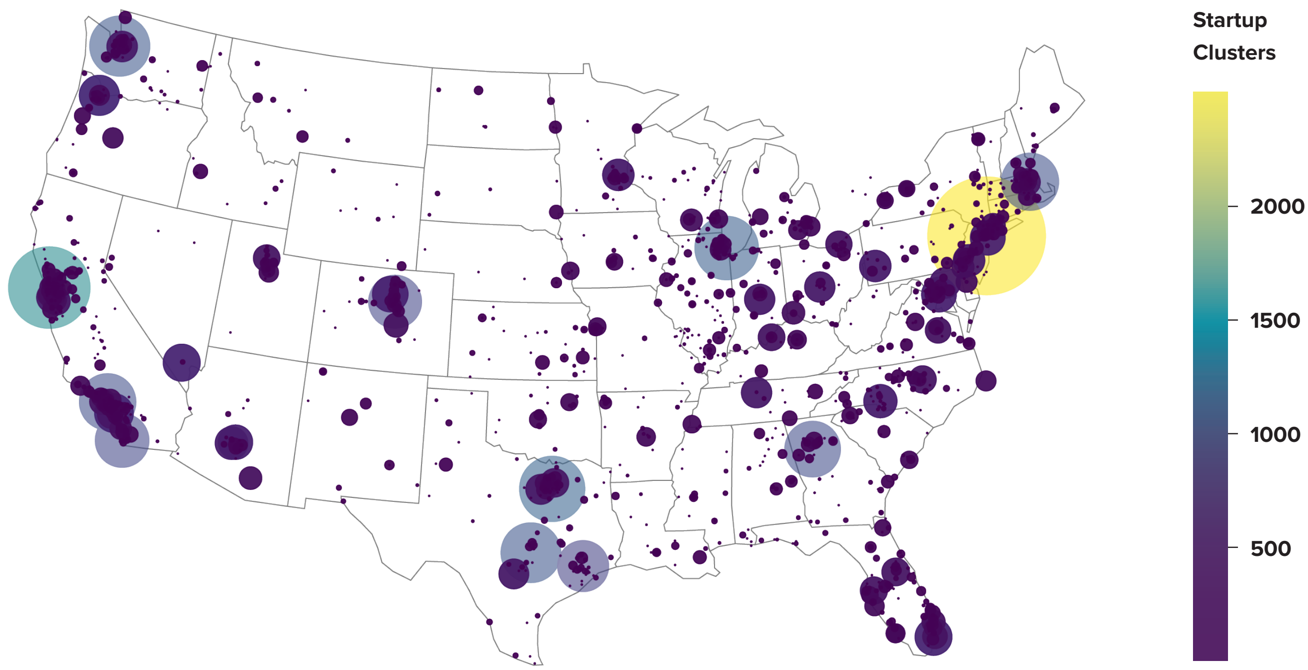
The U.S. is on the cusp of an entrepreneurial exponential curve, marked by a vibrant startup pipeline and driven by a surge in tech-oriented startups that have achieved remarkable successes. The startup ecosystem has also gained substantial momentum and is beginning to demonstrate its capacity to support a mosaic of thriving, scaling, and nascent startups. How can policy planners anticipate changes in employment demand as technology-enabled growth increases?

Inventorying the stock of emerging innovating firms is a first step to shed light on which cities are home to cradles of innovation—and perhaps more importantly, which communities are being left behind. Mapping innovation as it disperses across cities provides a mechanism to track unfurling trends and identify places of opportunity. However, policymakers may miss these gems if they deploy policy responses that are incompatible with local ecosystems or are otherwise inexpedient. Chasing ideations of tech-driven innovation is an inherently risky (and inefficient) strategy that can result in substantial wins or enormous losses. Instead, this paper argues that is better to: discern useful signals emitted by emerging industries; understand the technologies spurring their growth; anticipate new workforce demands; and synthesize these observations into policy prescriptions aimed at igniting the entrepreneurial spark indigenous to individual ecologies.

The geography of innovation is shifting, and the emergence of startup clusters is a prime signal of opportunity that should not be ignored, especially in places with shrinking options. We make extensive use of open-source data compiled using several strategies (including web scraping and natural language processing) to assemble data about the business of America's startups. Our search for innovation unearthed more than 33,000 young and scaling firms engaged in activities that cut across traditional industry silos.

So where are the sparks of the future? While obvious areas, like Silicon Valley and New York, still lead the nation as innovation hotbeds, there is good news for unlikely places. An emergence of distinct clusters is unveiling a trend that opposes the conventionally skewed tech-driven narrative. Traditional tech markets and other top-ranked metro areas are ceding ground to up-and-coming metro areas not traditionally associated with innovation, like Minneapolis and Charlotte (see Figure 1).

Figure 1. Mapping Innovation Startups. Tech-driven innovation is spreading from the east and west cradles, and some cities are leading over others. *Note: Brookings analysis of data collected from web scraping, YELP public API, FunDz propietary startup database.*



Emerging Innovation Cradles

Emerging places of innovation are notably smaller than the typical leaders. However, their capacity to support a vibrant startup ecosystem is undeniable.

New innovation cradles are making a grand entrance on the innovation hub scene and offer promising opportunities for startup pipelines and new job creation. But clusters are not permanent, and failure to adapt ecosystems to respond to innovation heralds a painful decline. As prominent labor economist Enrico Moretti observed, "Detroit's mistake was not the failure to stop the demise of jobs in auto manufacturing ... [the] mistake was its failure to redirect its ecosystem into something new when it still had an ecosystem." Innovation is volatile. Thus, cyclical cities and places equipped with flexible policies to capitalize on innovation determinants are best prepared to win the regeneration game.

Emerging places of innovation are notably smaller than the typical leader cities. However, their capacity to support a vibrant startup ecosystem is undeniable. Geographic de-concentrating of innovation hubs has significant implications for small and mid-sized cities, especially those challenged with balancing the competing needs of an innovation economy with those of low-income and working-class households. Many of these communities also happen to be most vulnerable to losing ground during this tech-driven transformation, which systematically disadvantages workers who are unable to adapt.

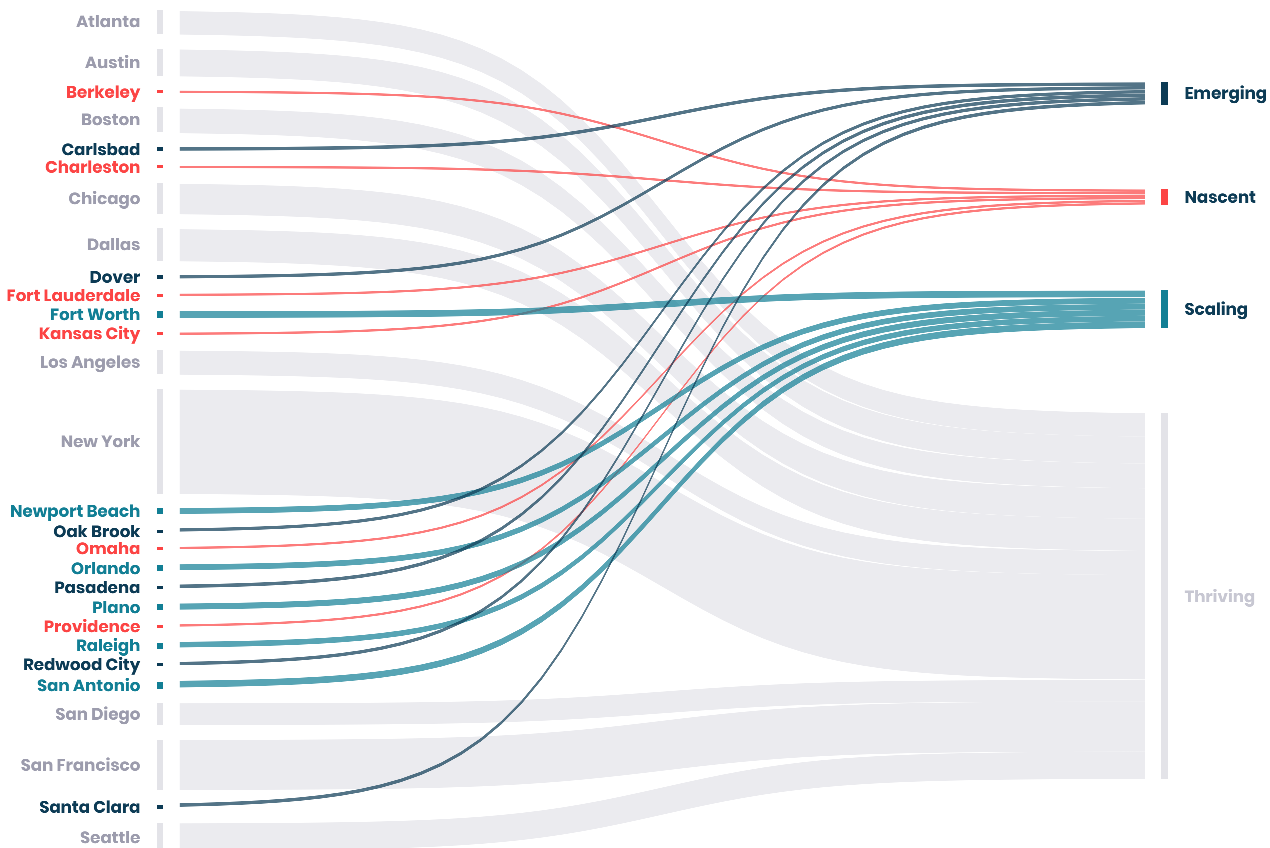
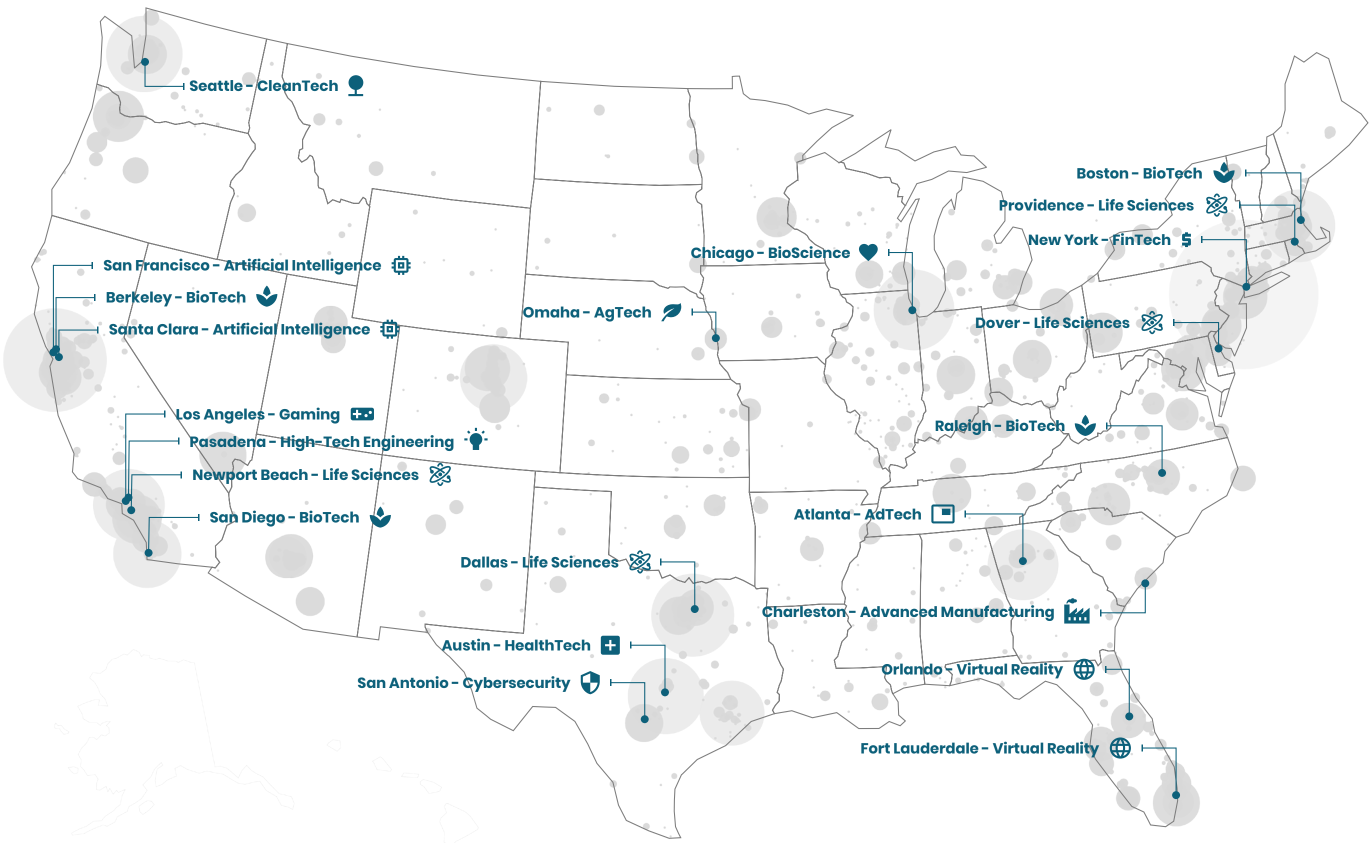


Figure 2. Rising innovation cities are making a grand entrance on the innovation hub. *Note: Brookings analysis of data collected from web scraping, YELP public API, FunDz propietary startup database.*

Focusing on leading cities alone masks other important locations, such as Washington, D.C., Philadelphia, and Baltimore, which have substantial Black populations. These cities are demonstrating their capacity to deliver innovation-driven growth and high-wage tech jobs. Inner cities are part of the innovation fabric, too. Brooklyn, N.Y., for example, hosts an estimated 210 startups, a figure that likely underestimates the true size of its ecosystem. While the inward spread from the coasts is welcome news, the innovation map shows that tech-driven growth is skipping large swaths of the country: Extensive parts of the Southwest, Rocky Mountains, and Midwest remain excluded from the surge.

Though interesting, mapping innovation solely by the inventory of startups within a city's borders does not paint a full picture; maps fall short in providing insight into a cluster's quality. To capitalize on innovation-driven opportunities, policymakers need to know more about the signals embedded in their innovation clusters, many of which are revealing themselves as highly specialized micro-industries that complement general industry verticals.

Figure 3. The diverse tapestry of innovation provides important signals about future workforce needs. *Note: Brookings analysis of open source database and 2017, Global Startup Ecosystem report.*



New Innovation Jobs

Innovation jobs, such as those within the innovation map's diverse high-tech clusters, are associated with a significant multiplier effect, according to Moretti. By his estimation, the impact of tech jobs in local ecosystems is substantial: One new tech job can generate 4.9 additional jobs in a city. An employment multiplier of this magnitude suggests that policy planners should be just as concerned with the kinds of startups incubating within their borders as they are with the sheer number. The U.S. stands at the center of a pivotal moment—one that implores society to consider what innovation and found jobs mean for marginalized groups.

When Uber debuted in 2009, no futurist could have predicted that a single startup could spawn the rideshare industry.

Industries have long shaped work and will continue to do so in the digital revolution. When Uber debuted in 2009, no futurist could have predicted that a single startup could spawn the rideshare industry. Numerous startup competitors have since entered this field, and automakers are now joining the market. A combination of GPS technology, artificial intelligence (AI), and machine learning made ridesharing possible, creating a cornerstone for the company's eventual scale. In addition to these critical technologies, a polyvalent workforce was a pivotal factor in Uber's success. In fact, the company's initial talent call was for software development talent—not drivers!

> **"[A]nybody have details on how the iPhone's Core Location algorithm actually functions?"**
> Travis Kalanick,
> Uber Co-Founder

Before Uber's first anniversary, the company's first chief executive officer, Ryan Graves, took to Twitter to announce his transition from a consulting career to a certified Apple developer: "I'm committing to… get[ting] through a few web/software development books…so that I can better understand the technologies I work with and the people I work with." Today, Uber's platform is supported by more than 12,000 employees across a fusion of talent: AI research scientists, autonomous vehicle hardware test engineers, digital designers, cloud security engineers, fintech business analysts, and of course, 1.5 million drivers. The rideshare industry, which includes Uber and its competitors, continues to seek an eclectic mix of workforce skills to support its explosive growth. At its core, innovation is about jobs and thus should stimulate urgent inquiries into emerging skill needs required to fuel its growth.

Next-Generation Labor Signals

The innovation wave surging across the U.S., whether driven by startups or incumbent multinational corporations, is changing demands for workforce talent.

The innovation wave surging across the U.S., whether driven by startups or incumbent multinational corporations, is changing demands for workforce talent. New industries and old ones seeking to reinvent themselves amid a technological shift are creating new dimensions of skill demand to match the surge's complexity. Innovation jobs and the skills required of an innovation workforce will be markedly different from those of the past; this is true from the nascent tech scene in Louisville, Ky., to the startup-revival in Detroit, where, according to EntryPoint, the birthrate of tech startups has grown by 54% since 2014.

Innovation has long been the mainstay of American prosperity and global competitiveness. While it is impossible to precisely forecast winning micro-industries, it is fair to assume that firms driving the surge will require a diverse and uniquely skilled workforce to fuel their growth. The workforce idea deserves careful attention because under the hood of Moretti's 5.0 tech job multiplier, discussed earlier, lies a two-pronged job creation process: Two of the newly created jobs will be tech positions, but the remaining three will be service-oriented jobs. Tech jobs provide a distinct income advantage. However, the picture is murkier for the newly found service-oriented jobs; these will be a combination of high-wage, high-skilled service positions, and low-wage, low-skilled ones. How can we ensure that today's low-skilled service workers, who are disproportionately Black, Hispanic, and Native American, are included in the higher-quality pipelines of tech-oriented and high-skilled service jobs?

Traversing Skill Bridges to Mobility in an Innovation Economy

This framework provides policy planners fine-grained visibility into the labor market, and a new opportunity to discern subtle trends, such as declining and emerging skills that can inform appropriate policy changes or prompt de nouveau formulations.

Fortunately, the skill signals of innovation jobs provide a blueprint for creating inclusion points for underrepresented minorities in high-value pipelines. However, policymakers need an enhanced understanding of the job market's skill infrastructure to draft the blueprint and create pipeline space for minorities. College degrees alone paint an incomplete picture.

METHODS AND DEFINITIONS

Exposing the labor market's skill infrastructure reduces information asymmetry and closes the gap between policy and reality. We analyze more than 20 million job postings to link innovation skills and inclusion. This framework provides policy planners fine-grained visibility into the labor market and a new opportunity to discern subtle trends, such as declining and emerging skills that can inform appropriate policy changes or prompt de nouveau formulations. Such a framework can dramatically enhance workers' agency, allowing them to self-sort into their "best fit" jobs and personalize their mobility.

Framing the skill infrastructure as a network of interrelationships between employer skill demands across occupations shows a striking pattern of non-linearity, and circular skill flows that better exemplify real-life models of work. We focus our attention primarily on hard skills such as JavaScript or project management; these skills have real meaning and tangible value for employers, making it easy to trace their fungibility across the network. Soft skills such as communication and critical thinking are difficult to define, and in our view, describe behavioral characteristics that are usually shaped by workplace context. Focusing on the interrelationships between employers' demand for skills and occupations reveals an intriguing fundamental: Skills are remarkably inter-operable across functional domains and can create bridges between professions traditionally viewed as unrelated or diametric opposites.

We leveraged the concept of skill inter-operability—that is, the extent to which skills are transferrable across occupations—to build sub-networks of occupations based on their skill similarities. These sub-networks are mostly communities of occupations clustered together as a result of their skill overlap.

Parsing skill-demand into a network of communities highlights the importance of possible skill connections, which are too often concealed by traditional linear analyses but are critical to connecting the dots between new skill-based opportunities and pathways.

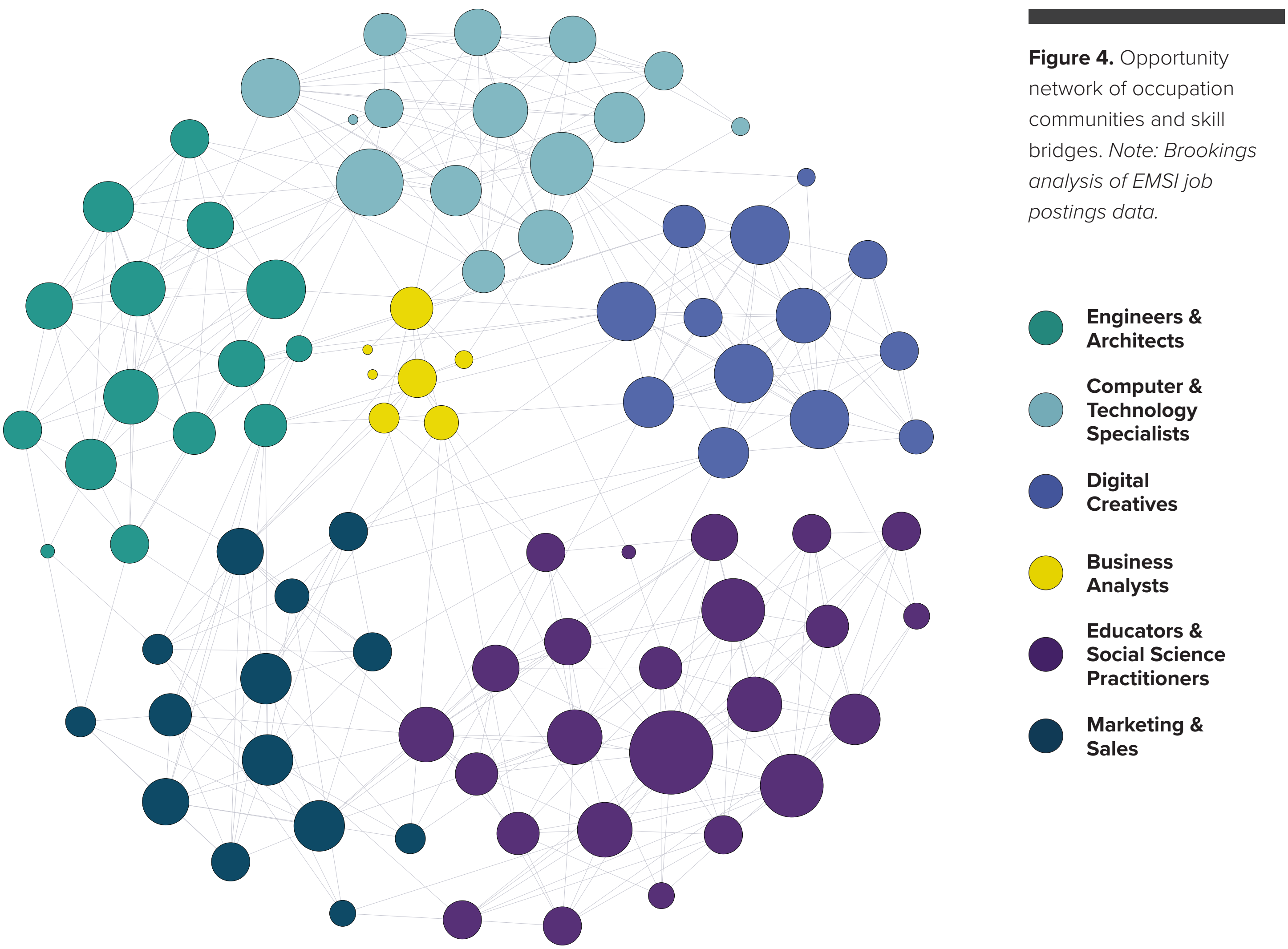
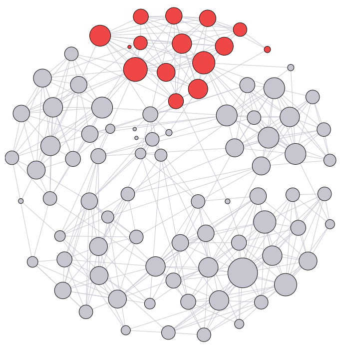


Figure 4. Opportunity network of occupation communities and skill bridges. *Note: Brookings analysis of EMSI job postings data.*



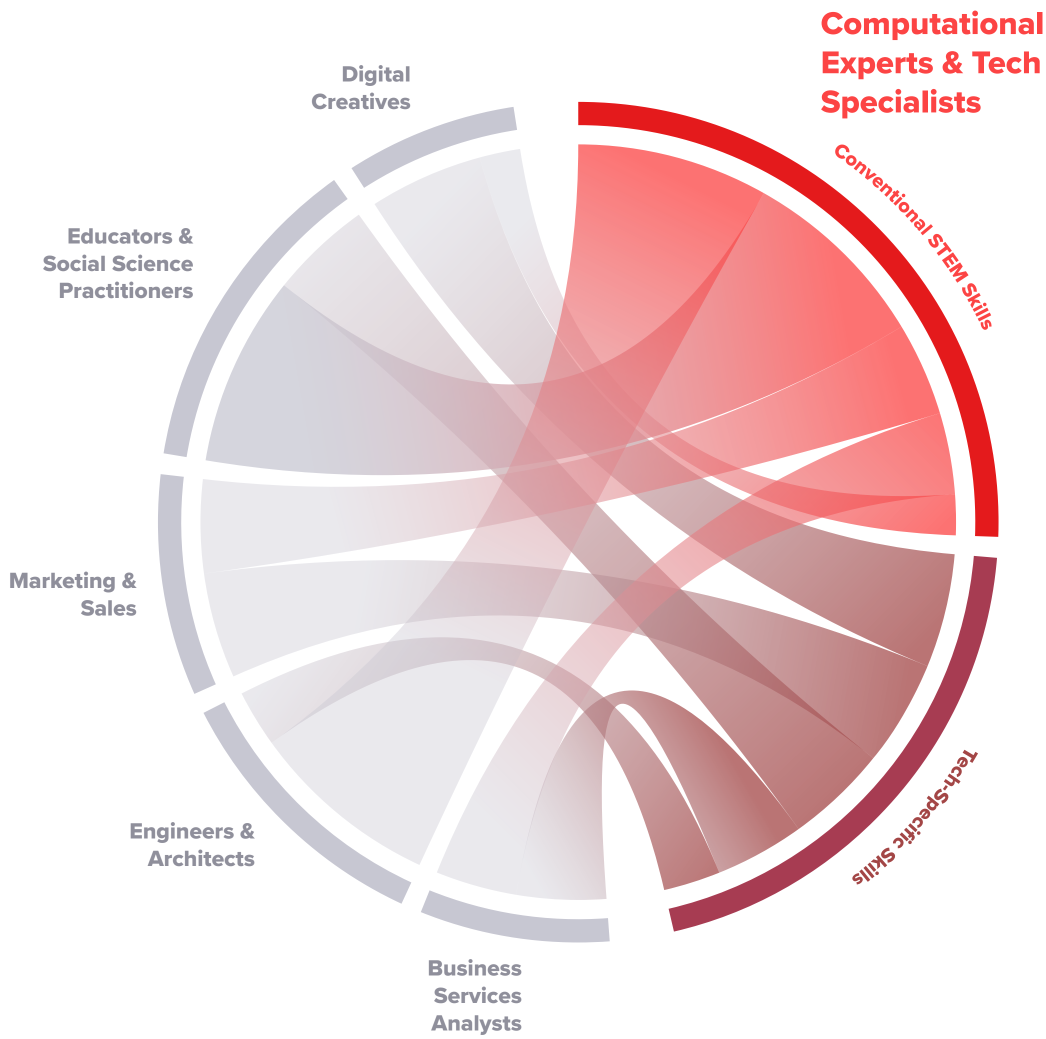
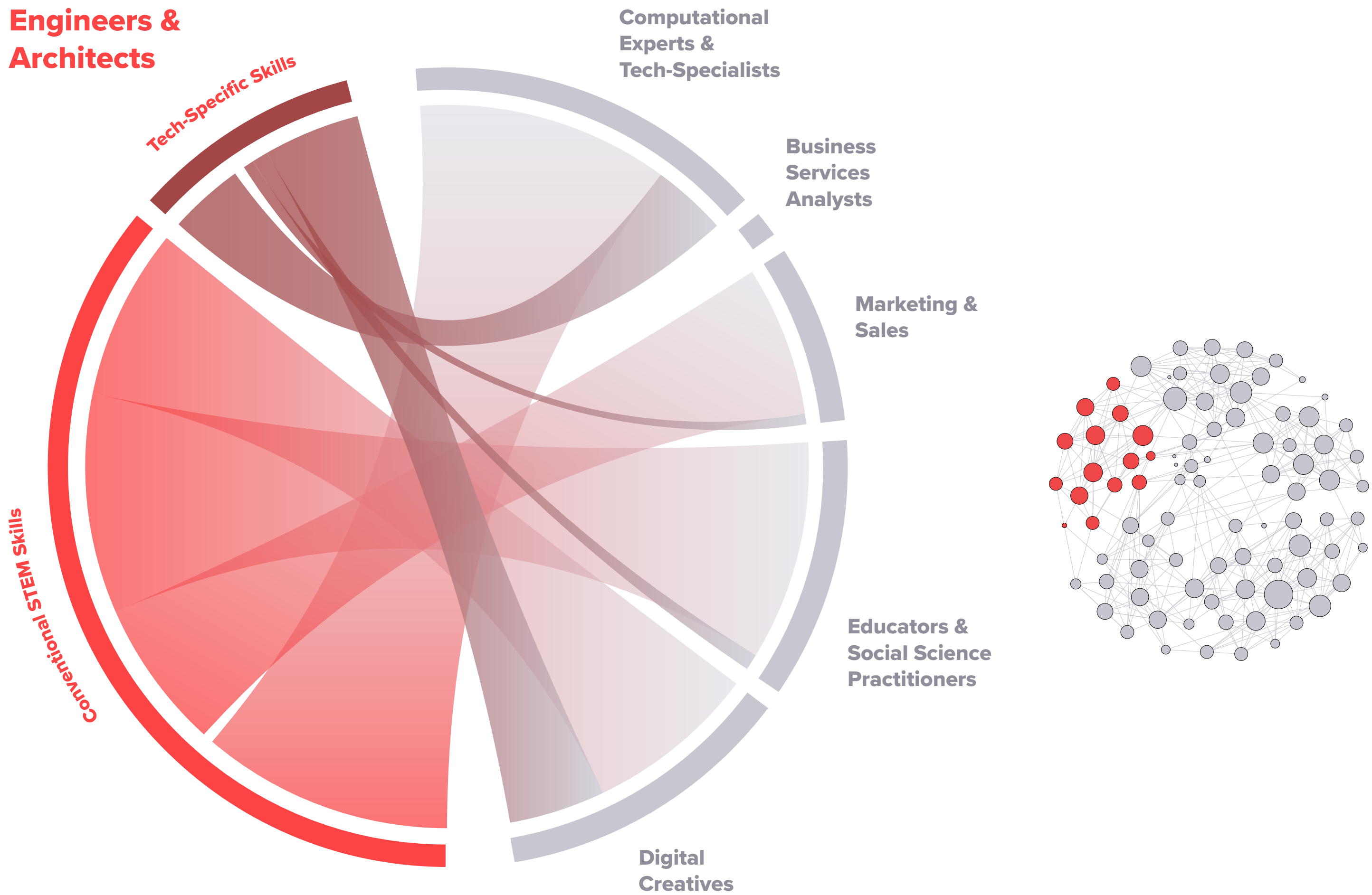


Figure 4a. Skill bridges between STEM and non-STEM occupations depict a bilateral skill flow. STEM and tech-specific skills that are central Computational and Tech experts are growing in relevance for non-STEM professions.

Figure 4 illustrates the results of our network analysis—six well-defined communities: Computing and Technology Specialists, Business Services Analysts, Engineers and Architects, Marketing and Sales, Educators and Social Science Practitioners, and Digital Creatives. Each node in the illustrated network represents a discrete occupation, and the links between them symbolize their skill-based relationship.

The Computing and Technology Specialist cluster captures a progression of tech-expertise; the group includes professions such as web developers, software developers, computer hardware engineers, and computer and information research scientists. Engineers and Architects share a considerable degree of skills with this community; the skills of community-technician-level trades—such as architectural and civil



drafters and electrical and electronics engineering technicians—place them in the same neighborhood as premium professions such as architects as well as industrial, mechanical, and civil engineers. The Digital Creatives cluster includes fine artists, multimedia artists and animators, and commercial and industrial designers. Likewise, the Business Services Analysts, Marketing and Sales, Educators and Social Science Practitioner communities are hosts to clusters of similarly skilled occupations.

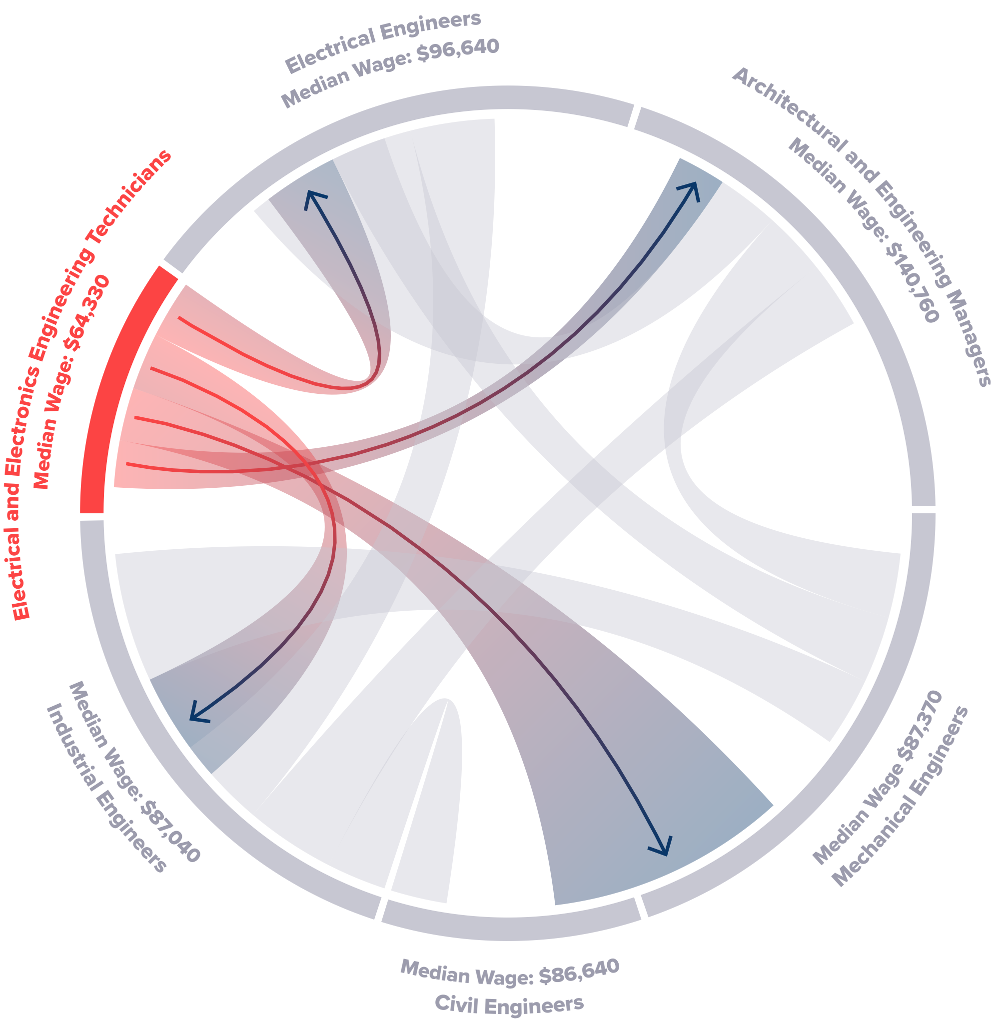
Figure 4b. Bilateral skill bridges between occupation communities show that non-STEM skills are critical for STEM professions as well.

Creating Skill Bridges

Mapping these skill similarities not only models the labor market in familiar ways, but it contextualizes the idea of skill interoperability. It's one thing to say that skills are portable, but it's quite another to expose the wireframe of this process and make transparent these connections that would otherwise remain invisible. A high-resolution picture of the potential transferability of skills can aid an individual worker in planning their career trajectory, which according to the Bureau of Labor Statistics can entail as many as 11.9 job changes over an individual's working life.

Increasing visibility into skill-bridges can facilitate targeted entry into and eventual traversal across clusters of skill-related occupations, which can provide meaningful starting points and pathway progressions to quality jobs. Figure 5 illustrates the possible flow of skills from the engineering technician entry point to other high-wage occupations within the Engineering and Architects cluster—a classic embodiment of mobility.

Figure 5. Skill portability represents actionable pathways to career and income mobility.



Bridge Node
Operations Research Analysts

Neighbor Node
Database Administrators

Composition of Inter-Community Skill Bridges

Conventional STEM	Tech-Specific	Non-STEM
17.1%	**18.8%**	**64.1%**
Sample Skills:	**Sample Skills:**	**Sample Skills:**
Biochemistry, Data Mining, Good Clinical Practices (GCP), Computer Hardware	Python, Power Business Intelligence (BI), Web Applications	Business Transformation, Integration Testing, Resource Allocation, Service Management

Skill overlaps do not mean that entire skill portfolios can be transitioned to a new career path. Transitioning from one related occupation to another invariably involves a sequence of re-training, re-skilling, or upskilling, but the magnitude of the shift is reduced substantially when skill overlap between occupations is high. Skill-bridges serve as information pipelines about transitions and potential occupational pairings. Engineers, for instance, cannot be easily transformed into animators without significant re-training and time costs; however, those finding it difficult to compete in saturated markets can increase their quality points by upgrading their skill portfolio with specific cross-functional (business and marketing) skills to increase employability odds.

Community pathways offer workers a nonlinear career trajectory that enables them to enrich their skill portfolios without starting over—a near impossibility for low-income individuals. Wielding skills to facilitate transversal across pathways opens new policy lenses for identifying skill-based entry points for workers and can lead to various job mobility possibilities.

Table 1a. Three-dimensional view of skill bridges between selected occupations: Operations Research Analysts and Database Administrators. *Note: A bridge node is an occupation from a non-STEM community comprised of overlapping skills (i.e. skill bridge) and forms a connection to occupations located in a STEM community; only select STEM occupations are responsible for the skill-bridge link and are defined as neighbor nodes since they complete the skill-bridge.*

Bridge Node
Sales Engineers

Neighbor Node
Software Developers, Systems Software

Composition of Inter-Community Skill Bridges		
Conventional STEM **24.8%**	**Tech-Specific** **25.6%**	**Non-STEM** **49.6%**
Sample Skills: Network Engineering, Network Routing, Research and Development, Robotics	**Sample Skills:** Computer-Aided Design, Virtualization, Wireless Networks, SystemVerilog	**Sample Skills:** Management, Product Lifecycle Management, Multitasking, Manufacturing Processes

Table 1b. Three-dimensional view of skill bridges between selected occupations: Sales Engineers and Software Developers, Systems Software.

Community pathways offer workers a nonlinear career trajectory that enables them to enrich their skill portfolios without starting over—a near impossibility for low-income individuals.

Skill–occupation networks offer a fresh perspective on modeling job market trends, but the real novelty of this approach lies in the skill-bridges that form potential pathways across the job communities. Skill-bridges show a flow of skills between core STEM-centric professions and non-technical occupations in non-STEM communities. These links show tighter connections between STEM and non-STEM jobs than conventional wisdom leads us to believe. These community-overlapping skills account for 18.5% of the hard skills in our database. In other words, the network contains a sizeable number of cross-functional skills that extend beyond conventional job contexts. Take, for example, AdRoll, an ad-tech marketing firm based in New York City. The company recruits for a mix of technical talent: product-marketing personnel and big-data engineers. Despite this new workforce need, marketing remains at the core of AdRoll's business and shapes its demand for people who can sell their marketing services. But there is a caveat: This sales workforce must possess a working knowledge of the software driving the company's technological edge. This blended skill signal—marketing and a "working knowledge of software"—is depicted in the network's skill-bridges and point to a broader trend: increasing demand for a blended skill taxonomy composed of traditional skills infused with tech skills, some of which are yet be defined.

Bridge Node
Management Analysts

Neighbor Node
Computer and Information Systems Managers

Composition of Inter-Community Skill Bridges

Conventional STEM 14.8%	Tech-Specific 11.9%	Non-STEM 73.3%
Sample Skills: Software Configuration Management, Lean Six Sigma, Software Quality Assurance (SQA)	**Sample Skills:** Dashboard, Data Architecture, Enterprise Application Platform, Data Management	**Sample Skills:** Acceptance Testing, Client Rapport, Competitive Intelligence, User Story

Table 1c. Three-dimensional view of skill bridges between selected occupations: Management Analysts and Computer and Information Systems Managers.

To understand the overarching taxonomy of the skill-bridges, we categorize each skill according to its relevance to the general STEM domain. As an illustration, we label chemistry as a STEM skill and business management as a non-STEM skill. We observed a three-dimensional skill-demand pattern of STEM, non-STEM, and tech-specific skills. On average, 28% of the bridge skills were foundational STEM skills, including statistics, biology, software engineering, chemistry, and applied mathematics.

Meanwhile, 18% of the bridge skills were tech-specific and related to specific software applications or programming languages. Specific technologies are driving labor market trends writ large; big data, cloud computing, and machine learning are increasingly shaping employers' demand for technical expertise to transform tech into improved business services and products. Non-STEM skills accounted for the remaining 54% of overlap. Skills like project management, project planning, research, and writing were nearly ubiquitous across the communities; general non-STEM skills are just as relevant to STEM occupations as the reverse. To illustrate: Multimedia artists and animators and web developers share some common skill traits, 59% of which are tech-specific skills—3D modeling, Adobe Illustrator, and QuarkXPress design software. However, non-STEM skills, such as compositions and painting, and STEM skills, such as software development and prototyping, were simultaneously relevant to both occupations—but to a lesser degree.

Employers are in the market for a tri-factor combination of foundational STEM and tech-specific skills, and non-STEM skills.

Bridge Node
Commercial and Industrial Designers

Neighbor Node
Industrial Engineers

Composition of Inter-Community Skill Bridges		
Conventional STEM 20.5%	**Tech-Specific** 22.3%	**Non-STEM** 57.1%
Sample Skills: Electrical Wirings, Materials Testing, Packaging and Labeling (Packaging Engineering)	**Sample Skills:** Adobe Creative Suite, JavaScript, Scrum (Software Development), Website Wireframe	**Sample Skills:** Benchmarking (Project Management), Market Research, Branding, Brochures

Table 1d. Three-dimensional view of skill bridges between selected occupations: Commercial and Industrial Designers and Computer and Industrial Engineers.

Employers are in the market for a tri-factor combination of foundational STEM and tech-specific skills, and non-STEM skills; of course, the proportional mix depends on the occupational context. It's crucial for policymakers to keep the topology of this skill mix in mind as they contemplate systemic updates to our workforce training models. Furthermore, the skill–job communities demonstrate that the pipeline involves more than STEM occupations alone, suggesting the need to broaden the tech-pipeline discourse to incorporate the inter-operability portability of skill blends.

Diversity policies aimed at including minorities in high-quality pipelines should prioritize programs that equip these individuals with skills relevant to fast-growing micro-industries and occupations. Community colleges such as Pennsylvania-based Thaddeus Stevens College of Technology (TSCT) offer inspirational models in that regard. TSCT seeded a new workforce training initiative in response to the manufacturing reshoring trend that brought high-wage, higher-skilled manufacturing jobs back to Lancaster County, York County, and surrounding areas. TSCT used its Trade Adjustment Assistance grant dollars from the Department of Labor to create new certificate programs and degree offerings, such as electro-mechanical technology, that provide critical skills upgrades to targeted groups: incumbent manufacturing workers, long-term unemployed, underrepresented minorities, and women. Crucially, multiple employer partners provide work-based training opportunities that function as direct

Bridge Node
Multimedia Artists and Animators

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Conventional STEM 15.7%	Tech-Specific 39.2%	Non-STEM 45.1%
Sample Skills: Analytics, Prototype (Manufacturing), Software Development	**Sample Skills:** 3D Modeling, Adobe Illustrator, Debugging, QuarkXPress Design Software	**Sample Skills:** Compositions, Painting, Systems Integration

Table 1e. Three-dimensional view of skill bridges between selected occupations: Multimedia Artists and Animators and Web Developers.

school-to-work pipelines, increasing the impact of the Department of Labor's programmatic subsidy.

Historically Black colleges and universities (HBCUs) and historically Hispanic colleges and universities (HHCUs) could adapt TSCT's model to reduce pipeline frictions for their graduates. For example, embedding idea-commercialization labs into engineering departments and mandating that all engineering students enroll in non-STEM courses—such as business management, product development, and introduction to R&D—would imbue HBCU and HHCU graduates with a competitive cross-disciplinary skill portfolio that couples foundational theoretical engineering training with job-market-ready tech and non-STEM skills. Newly minted HBCU and HHCU engineering graduates could then compete in the marketplace and find their "best fit" across an array of workforces, from Lockheed Martin to Nike's manufacturing and engineering team.

Equipping minorities with the appropriate balance of future-oriented skills is integral to solving the challenge of underrepresentation. Creating space for minorities within high-quality pipelines—tech, STEM, or otherwise—requires that policymakers embrace a skills-based theory of change that empowers marginalized groups to make data-driven decisions about fit within labor market and inform their demands for training to improve the odds of gainful employment and longevity.

Associates degrees are part of the policy solution when it comes to closing the skill gap and softening pipeline frictions.

Table 2. Skill Gap Index. *Notes: Brookings analysis of EMSI data.*

Occupation	Wages ($)	Projected Growth	Skill Gap Index
Computer and Information Research Scientists	118370	19.2	34.1
Architects, Except Landscape and Naval	79380	4.2	34.1
Architectural and Civil Drafters	54920	8.1	31.9
Computer Hardware Engineers	114600	5.5	30.9
Sales Engineers	101420	6.9	26.9
Information Security Analysts	98350	28.5	26.4
Operations Research Analysts	83390	27.4	26.3
Survey Researchers	57700	2.5	24.9
Computer Programmers	84280	-7.2	23.9
Computer Network Support Specialists	62770	8.3	23.8
Electronics Engineers, Except Computer	102700	3.7	23.8
Computer Network Architects	109020	6.5	23.6
Civil Engineers	86640	10.6	23.1
Database Administrators	90070	11.5	22.7
Medical Scientists, Except Epidemiologists	84810	13.4	22.5
Electrical and Electronics Engineering Technicians	64330	2	21.6
Life, Physical, and Social Science Technicians, All Other	49670	9.7	21.4
Mechanical Engineers	87370	8.8	21.3
Social Science Research Assistants	46640	4.3	21.3
Engineers, All Other	96980	6.4	20.3
Software Developers, Systems Software	110000	11.1	20.1
Web Developers	69430	15	19.5
Electrical Engineers	96640	8.6	18.1
Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	79680	5.1	17.9
Industrial Engineers	87040	9.7	17.7
Network and Computer Systems Administrators	82050	6.1	17.3
Computer User Support Specialists	50980	11.3	16.7
Software Developers, Applications	103620	30.7	16.3
Architectural and Engineering Managers	140760	5.5	16.0
Computer Occupations, All Other	90270	9.3	15.7
Registered Nurses	71730	14.8	14.8
Computer Systems Analysts	88740	9.1	14.5
Computer and Information Systems Managers	142530	12	14.4

Despite the good news and benefits associated with skill-portability, a sizeable skill gap limits the growth opportunities for workers and employers alike. Comparing the skills that employers need to fill their vacancies with the profile of workers currently employed in the field showed a fundamental disconnect between the skills that employers value and what the current workforce supplies. According to our estimated gap index, the number and type of skills that employers were seeking in the labor market went unmatched more than 20% of the time. This is a significant gap, and it aligns with frequently reported skill-mismatch complaints from employers.

The severity of the skill-mismatch varied widely and was particularly evident in core STEM occupations. For example, middle-skill occupations such as computer and information systems managers, computer systems analysts, and registered nurses exhibited below average gaps, ranging from 14.4% to 14.8%. However, occupations requiring complex, specialized skills—such as computer and information research scientists, computer hardware engineers, and architects—showed signs of acute skill-mismatches: The average gap for this cluster was 30.3%.

Skills are only part of job market dynamics. Employers typically signal their workforce needs through a combination of specific skill demands and degree credentials; here, too, we find gaps. Although mismatches between employers' demands and workforce degree credentials emerged, the gap was less severe than the estimated skill gap. Nevertheless, the two are related, and though the degree mismatch is a driving factor in the skill gap problem, it's also part of the solution. We find evidence that the mismatch for associate degrees was inversely related to the skill gap index: Increasing the number of workers with associate degrees narrowed the skill gap index by 13.6%.

Crucially, this finding supports the argument that associate degrees are part of the policy solution when it comes to closing the skill gap and softening pipeline frictions. This effect was especially pronounced for four occupations: registered nurses; architects (except landscape and naval); architectural and civil drafters; and electrical and electronics engineering technicians. For architectural drafters and registered nurses, employers' demand was 4.1 and 1.9 times the share of workers with associate degrees, respectively. Plainly, employers are demanding more workers with associate degrees than are being supplied for these occupations.
It is important to note that these occupations represent good jobs with strong incomes and bright futures, by Bureau of Labor Statistics projections.

Diversity policies aimed at including minorities in high-quality pipelines should prioritize programs that equip these individuals with skills relevant to fast-growing micro-industries and occupations.

Skills are Integral to Economic Mobility

Workers with stronger numeracy skills tend to earn a wage premium even after controlling for whether these workers are employed in a STEM occupation and have a college degree.

The skill-occupation communities highlighted the importance of STEM and tech-specific skills that, in combination, will play a critical role in unlocking opportunities throughout innovation hotspots and across emerging industries. However, shifting to a skills-driven workforce agenda will require assurances that these skills earn workers quality pay. We analyze the effect of STEM and tech-specific skills on workers' incomes to provide evidence-based support for policies aimed at building STEM-related skills. The Organization of Economic Co-Operation and Development's (OECD) Program for the International Assessment of Adult Competencies (PIAAC) provide valuable data to directly examine the relationship between workers' skills and their earning potential, as told from the supply side of the job market.

Even as we advocate for a broadened STEM agenda, we acknowledge that numeracy and STEM skills matter to workers' earning potential. Numeracy, according to the PIAAC survey, is a crucial link between worker incomes and the quality of their skill portfolios: Workers with stronger numeracy skills tend to earn a wage premium even after controlling for whether these workers are employed in a STEM occupation and have a college degree. This effect is significant even after controlling for demographic characteristics (education level, socio-economic background, gender, work experience, and race). However, certain STEM skills influence workers' earnings more than others.

All STEM skills are not created equal. Basic numeracy skills, like calculating costs, budgets, and completing simple arithmetic, have no effects on workers' earnings—but intermediate numeracy skills do. Employers are willing to reward workers if they can respond to their skill signals. Workers who are proficient in intermediate statistics and computational skills (e.g., algebra and manipulating formulas) and use these skills in their daily work generate a wage premium around 2.9% and 1.5%, respectively. Statistics is an interesting STEM domain that embodies an amalgam of reasoning, data interpretation, critical thinking, communication, and analytical skills that routinely top employers' wish lists, which perhaps explains the substantial income premium associated with the skill. What's more, statistics appeared in the network as a core STEM skill, with a high degree of inter-disciplinary relevance across STEM and non-STEM occupations alike.

Unsurprisingly, workers who are proficient in elite Information Computer and Technology (ICT) skills, such as a computer programming language, generate the highest skill-based return and earn a wage premium of approximately 3.4% in return for their investments. Although core STEM skills like statistics and programming may remain peripheral to most non-STEM disciplines, our network analyses suggest that they are valuable part of a workers' skill portfolios and their importance will continue to rise in the job market. Income premiums associated with STEM- and tech-oriented skills should not lead policymakers to conclude that STEM skills are the only worthwhile skills-based investments that deserve priority. Instead, policymakers should include broader skill-building strategies in their workforce agendas.

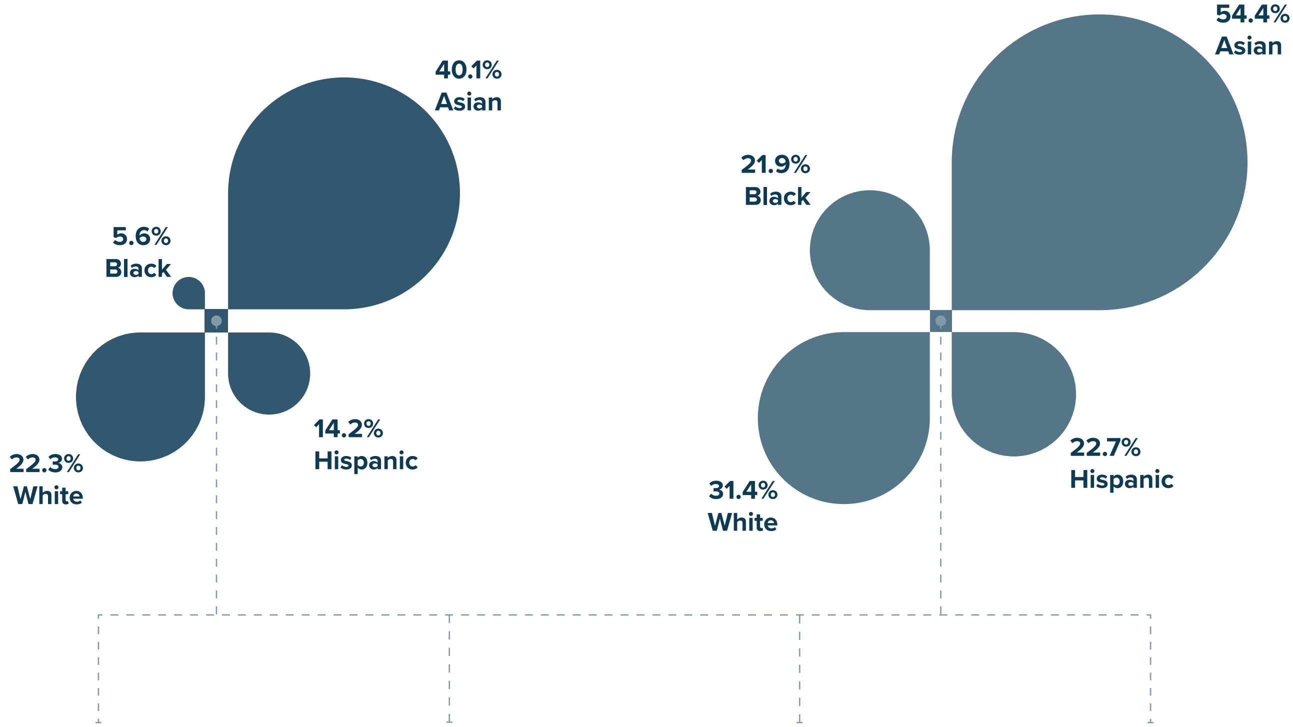
Skills-driven opportunities are dependent on the quality of workers' educational training and pathways. If higher-level STEM- and tech-specific skills enable workers to increase their earning potential, then purposeful modifications in education should promote these skills. However, any effort to advance these solutions must contend with stark inequities within the U.S. education system that preclude most minorities from enjoying the benefits of a well-intentioned STEM agenda, skill-based or otherwise.

Quantitative STEM skills (e.g., intermediate statistics and analysis) were associated with the highest wage premiums, but coincide with the lowest enrollment for Black, Hispanic, and Native American high school students. According to the National Center for Education Statistics, in 2009, these student groups showed the lowest enrollment in critical science and mathematics courses. Only 26.5% of Hispanic, 22.7% of Black, and 18.5% of Native American students were enrolled in critical intermediate level math courses; less than a quarter were taking foundational science classes (biology, chemistry, and physics). Mathematics enrollment among these minority high school students peaked in lower-level algebra and geometry classes, which, according to our analysis, are associated with either the lowest income premiums or none at all.

All STEM skills are not created equal. Basic numeracy skills such as calculating costs, budgets, and completing simple arithmetic have no effects on workers' earnings—but intermediate numeracy skills do.

Percent high school students enrolled in advanced mathematics
Pre-calculus, statistics, or calculus

Percent high school students enrolled in three core sciences
Biology, chemistry, and physics



Computer & Information Research Scientists
Median Wage - $118,370

Computer Hardware Engineers
Median Wage - $114,600

Information Security Analysts
Median Wage - $98,350

Operations Research Analysts
Median Wage - $83,390

Figure 6. High school exposure to foundational math and science courses is a critical stepping stone to high-wage occupations with high STEM skill demand. *Note: Native American students were excluded because data did not meet NCES reporting standards (too few cases for a reliable estimate).*

Like race and ethnicity, students' socio-economic backgrounds correlated with their access to critical courses. Just 25.5% of low-income students enroll in math analysis/pre-calculus, 5.1% take calculus, and 22.5% are in all three foundational science classes. Meanwhile, in each of these foundational areas, Asian American students over-index the national average enrollment by multiples of 1.7 and higher. The Asian American advantage in calculus is nearly three times the national average and seven times the enrollment rate of Black students. Furthermore, most Asian American students are enrolled in all three foundational science classes.

Mathematics

Student Demographics	Algebra I	Geometry	Algebra II/ Trigonometry	Analysis/ Pre-Calculus	Statistics	Calculus
Nationwide	68.9	88.3	75.8	35.3	10.8	15.9
Panel A: Socioeconomics — Percent of Students Eligible for Free or Reduced-Price Lunch						
0-25%	61.3	89.7	80.1	43.1	14.8	22.6
26-50%	70.9	88.4	74.7	29.7	8.6	11.8
51-75%	75.8	87.4	69.3	25.4	7.5	9.8
76-100%	80.1	88.8	70.7	25.5	5.1	7.5

Science

Student Demographics	Biology	Chemistry	Physics	Biology & Chemistry	Chemistry & Physics
Nationwide	95.6	70.4	36.1	68.3	30.1
Panel B: Socioeconomics — Percent of Students Eligible for Free or Reduced-Price Lunch					
0-25%	96.4	76.3	46.5	74.9	40.4
26-50%	94.5	64.0	27.6	61.6	22.2
51-75%	95.6	65.6	29.4	64.2	22.7
76-100%	95.6	69.4	26.6	68.2	22.8

Table 3. High School Student Enrollment in Mathematics and Science Courses: 2009. *Source: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, High School Transcript Study (HSTS), various years, 1990-2009.*

Calculus, biology, chemistry, and physics are critical pre-requisites for students aspiring to pursue computer science or an engineering-related discipline at the college or university level, and are also crucial stepping stones to high-wage STEM jobs. Students with access to critical STEM courses and skills beyond algebra are well positioned to earn income premiums upon entering the job market. Solutions aimed at minority pipeline issues must include policies to remedy inequitable access to critical math and science classes at the high school level. Without leveling the playing field for Black, Hispanic, and Native American students, the pipeline problem for these minority groups will persist.

Inclusion Opportunities

Solving the pipeline problem for minorities will require shifting away from generic STEM policies toward interventions targeted to specific opportunities.

Innovation hotspots are creating robust job opportunities across the U.S., but it is up to policymakers to translate these innovation signals into inclusive opportunities for underrepresented minorities. The minority pipeline problem is not a myth; it is a consequence of a combination of factors, including discrimination. Proactive policies improve the odds of an inclusive labor market, however, solving the pipeline problem for minorities will require shifting away from generic STEM policies toward interventions targeted to specific opportunities. Surgically targeting occupations with systematic skill gaps, strong employment projections, and correspondingly high wages provides a blueprint for policymakers to select pipeline starting points consistent with the workforce needs of employers local to their innovation ecosystems. According to our analysis, four occupations stand out as potential growth pipelines to create quality opportunities for underrepresented minorities: computer hardware engineers, computer information scientists, information security analysts, and operations research analysts.

HIGH-SKILLED PIPELINES

Computer hardware engineers and computer information scientists earn the highest median wages among occupations with an acute skill gap index, indicating a clear market need for skilled workers in these occupations. However, Black and Hispanic populations account for no more than 6.9% and 8.0% of these positions on average, respectively, even though they comprise 11.9% and 7.0% of students graduating with high-demand advanced degrees in computer and information sciences, computer science, and information technology. Asian American workers out-index Black and Hispanic workers in these two occupations.

Policies should aim to increase Black and Hispanic representation in these occupations, but benchmark their employment representation to that of their Asian American peers.

Quantitative STEM skills were associated with the highest wage premiums, but coincide with the lowest enrollment for Black, Hispanic, and Native American high school students.

Figure 7. Opportunity pipelines embedded in the occupation network represent gateway pathways for targeted inclusion policies.

Engineers & Architects

Computer & Technology Specialists

Digital Creatives

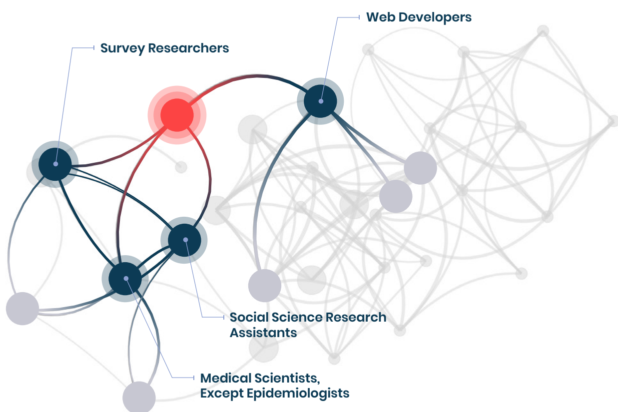
Business Analysts

Educators & Social Science Practitioners

Marketing & Sales

Figure 8. Bridge node detail: Computer and Information Research Scientists.

Computer and Information Research Scientists



MEDIAN WAGE	$118,370
PROJECTED GROWTH	19.2%
SKILLS GAP INDEX	34.1%

Employer Demand for College Degrees

Associate's	Bachelor's	Master's	Ph.D./Professional
0.2%	25.7%	37.4%	36.1%

Employment Demographics

White	Black	Asian	Hispanic
69.5%	6.95%	21.6%	1.93%

Worker Degree Distribution

Associate's	Bachelor's	Master's	Ph.D./Professional
0.8%	44.9%	30.5%	23.1%

Top Two Degrees Employers Demand

Master's Degree	Ph.D. or Professional Degree

Popular Majors (CIP Code)

- Computer and Information Sciences, General (11.0101)
- Computer Science (11.0701)
- Information Technology (11.0103)

Master's Degree Demographics

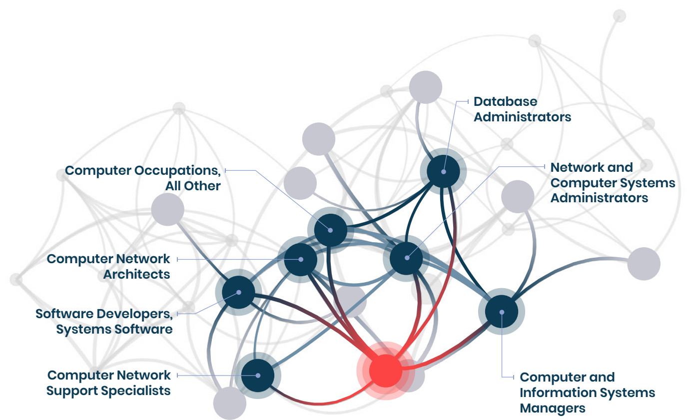
White	53.2%
Black	11.9%
Asian	27.6%
Hispanic	7.0%
Native American	0.5%

MIDDLE-SKILLED PIPELINES

Information security analysts and operations research analysts are occupations with relatively high median wages that are expected to undergo explosive employment growth; the Bureau of Labor Statistics projected that employment in these occupations would balloon by 28.5% and 27.4%, respectively, between 2016 and 2026. According to the presented skill gap index, employers are facing substantial challenges finding the skills they need.

Figure 9. Bridge node detail: Information Security Analysts.

Information Security Analysts



MEDIAN WAGE	$98,350
PROJECTED GROWTH	28.5%
SKILLS GAP INDEX	26.4%

Employer Demand for College Degrees

Associate's	Bachelor's	Master's	Ph.D./Professional
3.0%	72.5%	16.8%	3.0%

Employment Demographics

White	Black	Asian	Hispanic
76.8%	12.3%	8.5%	6.8%

Worker Degree Distribution

Associate's	Bachelor's	Master's	Ph.D./Professional
6.5%	63.4%	26.3%	2.5%

Top Two Degrees Employers Demand

Bachelor's Degree	Master's Degree

Popular Majors (CIP Code)

- Computer and Information Sciences, General (11.0101)
- Information Technology (11.0103)
- Computer Systems Networking and Telecommunications (11.0901)

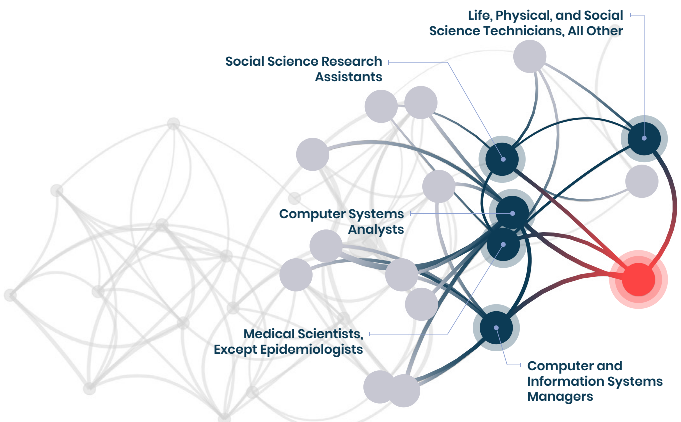
Bachelor's Degree Demographics

White	59.2%
Black	10.4%
Asian	13.1%
Hispanic	16.9%
Native American	0.5%

Figure 10. Bridge node detail: Operations Research Analysts.

However, white employment is more than 2.5 times the employment share of Asian American, Black, and Hispanic communities, who, on average, account for 9.2%, 11.6%, and 8.4% of employees in these occupations, respectively. Policies should be focused on all minorities in these occupations and aim to increase Black, Hispanic, and Asian American representation relative to their white counterparts.

Operations Research Analysts



MEDIAN WAGE	**$83,390**
PROJECTED GROWTH	**27.4%**
SKILLS GAP INDEX	**26.3%**

Employer Demand for College Degrees

Associate's	Bachelor's	Master's	Ph.D./Professional
3.3%	66.2%	19.4%	3.3%

Employment Demographics

White	Black	Asian	Hispanic
76.9%	10.9%	9.8%	9.9%

Worker Degree Distribution

Associate's	Bachelor's	Master's	Ph.D./Professional
3.9%	66.8%	25.2%	2.9%

Top Two Degrees Employers Demand

Bachelor's Degree	Master's Degree

Popular Majors (CIP Code)

- Management Science (52.1301)
- Management Sciences and Quantitative Methods, Other (52.1399)

Bachelor's Degree Demographics

White	66.3%
Black	7.1%
Asian	17.0%
Hispanic	9.4%
Native American	0.3%

Strengthening Opportunities for Native Americans

Native Americans face the worst odds throughout the entire pipeline, from unequal access to important science and math courses to STEM major degrees and finally to workforce penetration in high-opportunity occupation nodes.

Native Americans face the worst odds throughout the entire pipeline, from unequal access to important science and math courses to STEM major degrees to workforce penetration in high-opportunity occupation nodes. Policymakers whose constituents include substantial Native American populations should create policies targeted to this population at the secondary and postsecondary levels, as well as within workforce diversity initiatives.

Occupations at the associate-degree level represent crucial on-ramp entry points, opening tangible pathways to employment opportunities and income mobility. While employers preferred bachelor's degrees in most occupations, there are several where employers expressed a strong preference for associate degrees, including architectural and civil drafters, electrical and electronics engineering technicians, and registered nurses. Increasing the share of Native Americans in these occupation pipelines could be accomplished reasonably quickly relative to other occupations that require longer-term degrees, and they could deliver returns in a shorter time frame.

Engineering and drafter technicians are accessible entry points that are well-suited to skill-training programs such as EdX certificates, tech-certification badges, and other shorter-term certificate programs that can deliver foundational training alongside vocational skills trained on relevant technologies. Additionally, as evidenced by the skill–occupation networks, skills acquired in one occupation are transferrable to connected, higher-paying ones with which they share a high degree of skill similarity. Employees trained in the right skill-mix for these jobs stand a good chance of capturing employment opportunities with strong incomes.

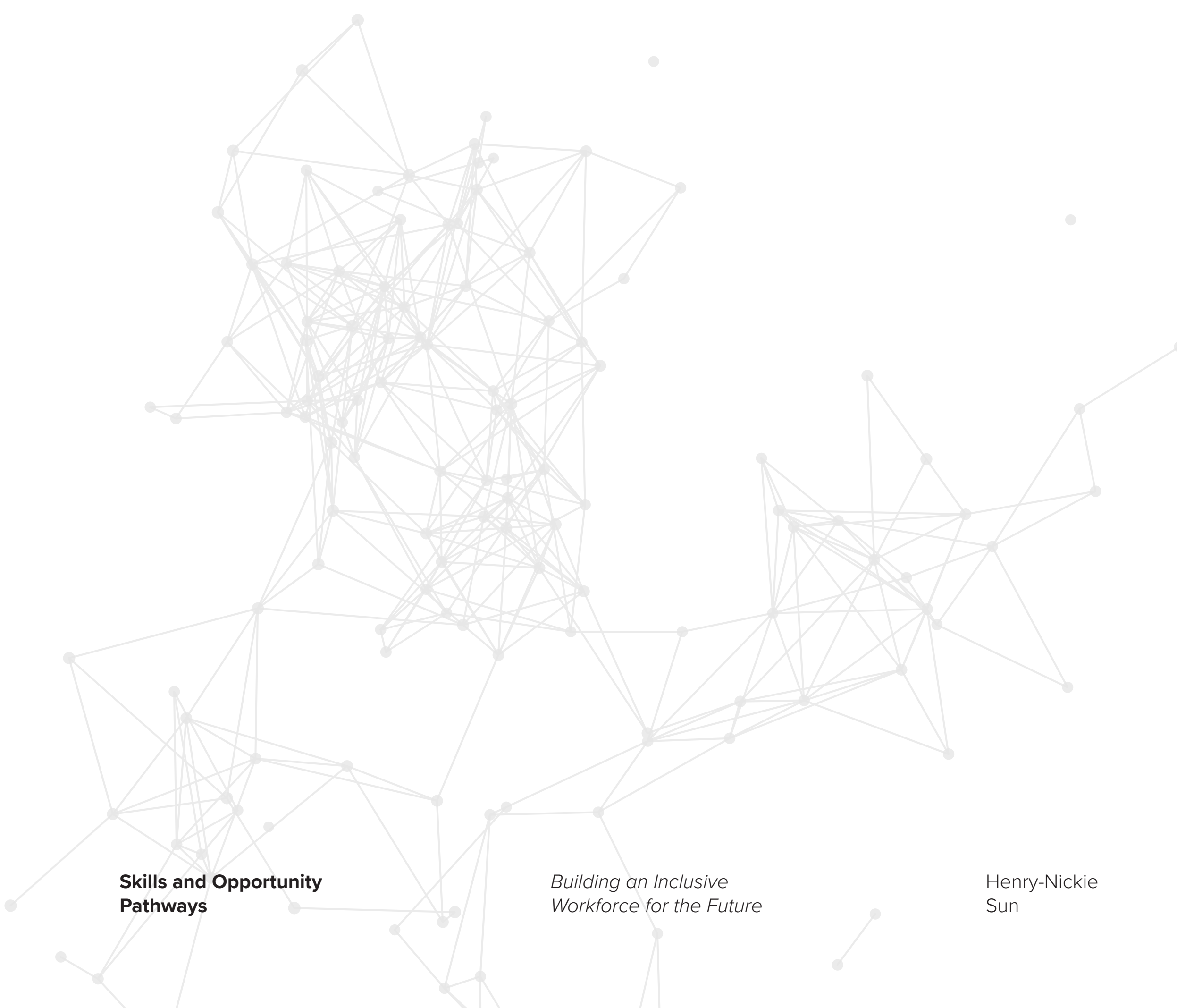
Conclusion

Solving the STEM pipeline problem requires a multi-pronged approach to level the playing field.

This report presents a framework that innovatively engages education policymakers and workforce planners. A skills-based topological examination of the job market provides a nuanced way for policy planners to assess the scale and breadth of emerging trends within local job markets and formulate policy responses that support workers and their innovation ecosystems. Projecting labor market data onto a network reveals specific pipeline junctures well-suited to high-impact, inclusionary policy strategies.

Skill–occupation networks and skill gaps make clear that solving the STEM pipeline problem requires a multi-pronged approach to level the playing field. Including minorities in the innovation economy requires that Black, Hispanic, and Native American students have equitable access to core math and science training that, at a minimum, puts them on par with their Asian American peers.

Raising the absolute numbers of minority STEM graduates and employees will increase their representation in core STEM occupations, but these policies alone are insufficient to address pipeline flows. Instead, policymakers need to broaden their toolset to include holistic policies that strategically enhance minorities' skill competitiveness and close crucial STEM education gaps.



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Acknowledgement

Apple, Google, and Lockheed Martin provide general, unrestricted support to The Brookings Institution. The findings, interpretations, and conclusions posted in this piece are not influenced by any donation. Brookings recognizes that the value it provides is in its absolute commitment to quality, independence, and impact. Activities supported by its donors reflect this commitment.

The authors would like to thank Brookings colleagues Camille Busette, Nicol Turner Lee, and Kwadwo Frimpong for their insightful contributions, assistance, and support.

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Report layout and graphics by Objectively.

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Skills and Opportunity Pathways

Building an Inclusive Workforce for the Future

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Appendix 1

Complete table of pattern skill flows underlying the skill-bridges linking STEM and non-STEM occupations

Bridge Node
Art Director

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM 7.9%	Tech-Specific 28.6%	Non-STEM 63.5%
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Configuration Management, Lean Six Sigma, Software Configuration Management, Software Quality Assurance (SQA)	Dashboard, Data Architecture, Data Management, Enterprise Application Platform	Acceptance Testing, Aerial Work Platforms, Business Transformation, User Story

Bridge Node
Commercial and Industrial Designers

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM 14.9%	Tech-Specific 29.7%	Non-STEM 55.4%
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Benchmarking (Computing), Geometry, Packaging And Labeling, Software Quality Assurance (SQA)	Adobe Creative Suite, Adobe Illustrator, Enterprise Resource Planning, Web Pages	Benchmarking (Project Management), Market Research, Navigation, Outsourcing

Bridge Node
Commercial and Industrial Designers

Neighbor Node
Industrial Engineers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
20.5%	**22.3%**	**57.1%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Benchmarking (Computing), Sociology, Software Development Life Cycle	Adobe Illustrator, Google Analytics, Web Content Management Systems, Web Pages	Benchmarking (Project Management), Google AdWords, Market Research

Bridge Node
Fine Artists, Including Painters, Sculptors, and Illustrators

Neighbor Node
Architects, Except Landscape and Naval

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
11.8%	**58.8%**	**29.4%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Information Systems, Landscaping	3D Modeling, Adobe Illustrator, Debugging, QuarkXPress Design Software	Creative Writing, Systems Integration, Marketing Communications,

Bridge Node
General and Operations Managers

Neighbor Node
First-Line Supervisors of Production and Operating Workers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
16.4%	**0.5%**	**74.3%**
Top STEM Skills: Algebra, Environmental Compliance, Methods of Production, Statistics	**Top Tech Skills:** Microsoft Access	**Top Non-STEM Skills:** Business Process, Construction Management, Regulatory Compliance, Operating Budget

Bridge Node
Graphic Designers

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
6.5%	**28.3%**	**65.2%**
Top STEM Skills: Functional Design, Mobile Data, Software Documentation, Prototyping	**Top Tech Skills:** Adobe Creative Suite, HTML5, WebPages, Web Publishing	**Top Non-STEM Skills:** Industry Practices, Navigation, Outsourcing

Bridge Node

Life, Physical, and Social Science Technicians, All Other

Neighbor Node

Medical Scientists, Except Epidemiologists

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
60.5%	**3.9%**	**35.5%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Biochemistry, Cell Biology, Good Clinical Practices (GCP), ICH Guidelines	Data Collection, Mapping, Microsoft Access	Food Services, Immigration, Material Safety Data, Client Rapport

Bridge Node

Management Analysts

Neighbor Node

Computer and Information Systems Managers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
14.8%	**11.9%**	**73.3%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Configuration Management, Lean Six Sigma, Software Configuration Management, Software Quality Assurance (SQA)	Dashboard, Data Architecture, Data Management, Enterprise Application Platform	Competitive Intelligence, Product Lifecycle, Refining, Workforce Planning

Bridge Node
Management Analysts

Neighbor Node
Database Administrators

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
20.4%	**18.5%**	**61.1%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Data Mining, Information Technology Consulting, Joint Application Design, Software Documentation	JavaScript (Programming Language), Microsoft Visual Studio, Pivot Table, Python (Programming Language), Teradata SQL	Business Transformation, Job Scheduling (Inventory Management), Reporting Tools,Product Software Implementation Method

Bridge Node
Multimedia Artists and Animators

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
15.7%	**39.2%**	**45.1%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Analytics, Prototype (Manufacturing), Prototyping, Software Development Life Cycle	Adobe Creative Suite, Adobe Illustrator, Adobe Photoshop, Scripting	Compositions, Hosting, Painting, Systems Integration

Bridge Node
Operations Research Analysts

Neighbor Node
Database Administrators

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
17.1%	**18.8%**	**64.1%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Computer Hardware, Data Mining, Electronic Medical Record, Engineering Management	Microsoft Visual Studio, Pivot Table, Power BI, Web Applications	Integration Testing, Resource Allocation, Service Management, Systems Integration

Bridge Node
Public Relations Specialists

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
12.2%	**18.4%**	**69.4%**
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Benchmarking (Computing), Packaging And Labeling, Sociology, Software Development Life Cycle	Adobe Illustrator, Google Analytics, Web Content Management Systems, Web Pages	Benchmarking (Project Management), Google AdWords, Market Research, Outsourcing

Bridge Node
Sales Engineers

Neighbor Node
Software Developers, Systems Software

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
24.8%	25.6%	49.6%
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Network Engineering, Network Routing, Research And Development, Robotics	Computer-Aided Design, Peripheral, SystemVerilog, Virtualization, Wireless Networks	Account Management, Conflict Resolution, Multitasking, Product Management

Bridge Node
Technical Writers

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM	Tech-Specific	Non-STEM
25.0%	30.7%	44.3%
Top STEM Skills:	**Top Tech Skills:**	**Top Non-STEM Skills:**
Benchmarking (Computing), Computer Control Systems, Electronic Engineering, Infrastructure As A Service (IaaS)	Adobe Illustrator, Data Management, Middleware, Visual Basic .NET (Programming Language)	Benchmarking (Project Management), Industry Practices, Safety Assurance, User Story

Bridge Node
Writers and Authors

Neighbor Node
Web Developers

Composition of Inter-Community Skill Bridges

Foundational STEM 6.8%	Tech-Specific 28.8%	Non-STEM 64.4%
Top STEM Skills: Analytics, Packaging And Labeling, Social Sciences, Sociology	**Top Tech Skills:** Adobe Creative Suite, Adobe Illustrator, Google Analytics, Web Pages	**Top Non-STEM Skills:** Creative Writing, Marketing Communications, Professional Services

Skills and Opportunity Pathways

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Appendix 2

Statistical relationship between workers' skills and gross hourly earnings

	Workers Gross Hourly Earnings				
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Numeracy Skills	0.245***			0.135***	0.119***
	(0.003)			(0.002)	(0.003)
STEM Occupation		0.414***	0.286***	0.260***	0.208***
		(0.003)	(0.004)	(0.004)	(0.004)
College Degree			0.386***	0.307***	0.275***
			(0.003)	(0.004)	(0.004)
Work Experience			0.036***	0.036***	0.034***
			(0.000)	(0.000)	(0.001)
SES Index			0.034***	0.016***	0.008***
			(0.001)	(0.001)	(0.001)
Gender			0.179***	0.142***	-0.141***
			(0.003)	(0.003)	(0.003)
Minority			-0.076***	-0.004	-0.020***
			(0.004)	(0.004)	(0.003)
Basic Computational					0.001
					(0.001)
Intermediate Algebra					0.019***
					(0.001)
Intermediate Statistics					0.031***
					(0.001)
Advanced Math					0.008***
					(0.002)
ICT Programming					0.034***
					(0.001)
Work Experience Quadratic	No	No	Yes	Yes	Yes
Obs.	3142	3042	3039	3039	2401
R-squared	0.160	0.066	0.282	0.312	0.299

Notes.

1. Wage is the log transformation of hourly earnings, excluding wages and bonuses for salary earners. The sample includes working adults 24 years and older. Regressions are ordinary least squares estimations; results are reported for sample weighted estimates. The numeracy variable comprises plausible value estimates for OECD PIAAC measures.
2. Standard errors are in parenthesis.
3. ***p<0.01, ** p<0.05, * p<0.1

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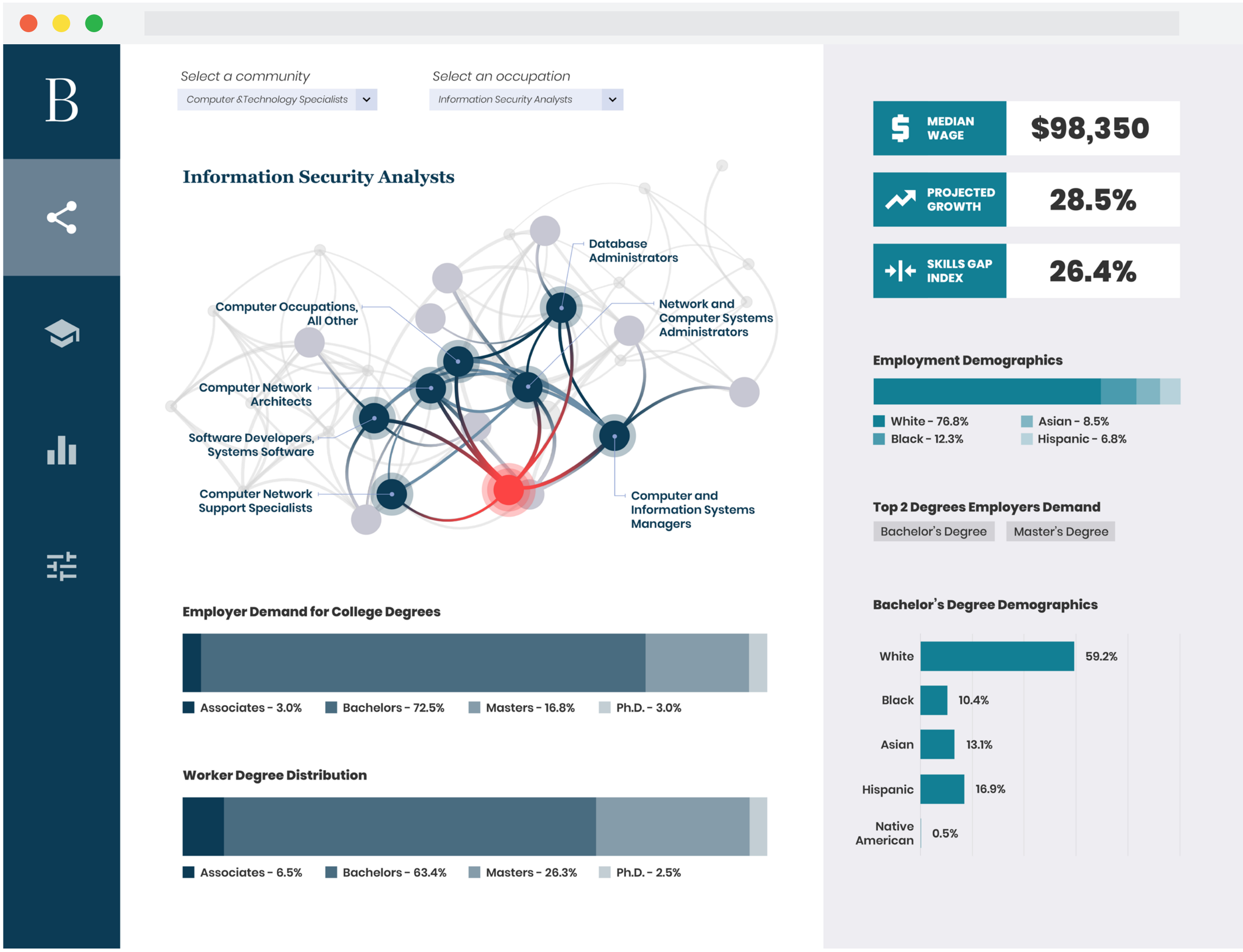
Appendix 3

Mockup of a workforce dashboard tool that enables a deepened, network view of potential occupation pipeline opportunities, skill requirements, and pathway possibilities


B
Select a community
Computer & Technology Specialists
Select an occupation
Information Security Analysts
Information Security Analysts
Database Administrators
Computer Occupations, All Other
Network and Computer Systems Administrators
Computer Network Architects
Software Developers, Systems Software
Computer Network Support Specialists
Computer and Information Systems Managers
Employer Demand for College Degrees
Associates - 3.0%
Bachelors - 72.5%
Masters - 16.8%
Ph.D. - 3.0%
Worker Degree Distribution
Associates - 6.5%
Bachelors - 63.4%
Masters - 26.3%
Ph.D. - 2.5%
MEDIAN WAGE
$98,350
PROJECTED GROWTH
28.5%
SKILLS GAP INDEX
26.4%
Employment Demographics
White - 76.8%
Asian - 8.5%
Black - 12.3%
Hispanic - 6.8%
Top 2 Degrees Employers Demand
Bachelor's Degree
Master's Degree
Bachelor's Degree Demographics
White 59.2%
Black 10.4%
Asian 13.1%
Hispanic 16.9%
Native American 0.5%

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