WHAT JOBS ARE AFFECTED BY AI?

Better-paid, better-educated workers face the most exposure

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November 2019

Metropolitan Policy Program
at BROOKINGS

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Introduction

The debate between experts over how automation will affect the future of work has been one of the most active cottage industries in labor economics in recent years. Numerous scholars forecast major disruptions of human work; others minimize those impacts.

And yet, the field has nevertheless managed to generate a number of shared insights, with none more consistent than the finding that least well-off will suffer automation's greatest shocks on the labor market.

"The vulnerable will be the most vulnerable" was a key takeaway of the report on AI and automation we released earlier this year, for example. That analysis, based on forecasts of occupation-level automation exposure from expert assessment by the McKinsey Global Institute, showed that higher-wage, better-educated workers will largely make out alright as automation spreads. This result was not an outlier. Similar findings have accumulated in numerous reports, ranging from those by teams at Oxford University and the OECD to the African American Mayors Association.

But what about artificial intelligence (AI), the increasingly powerful form of digital automation using machines that can learn, reason, and act for themselves?

In recent years, AI applications have generated increasing interest in "future of work" discussions as the technology achieved superhuman performance in a range of valuable tasks, from radiology to legal contracts. However, it has been difficult to get a specific read on AI's implications on the labor market.

In part because the technologies have not yet been widely adopted, analyses such as Brookings's or those from Oxford, OECD, and McKinsey have had to rely either on case studies or subjective assessments by experts to determine which occupations might be susceptible to an AI takeover. What's more, none of these analyses focused solely and specifically on AI. Instead, most research has concentrated on an undifferentiated array of "automation" technologies including robotics, software, and AI all at once. The result has been a lot of discussion—but not a lot of clarity—about AI, with prognostications that range from utopian to apocalyptic.[1]

But now comes a new approach. By quantifying the overlap between the text of AI patents and the text of job descriptions, Stanford University Ph.D. candidate Michael Webb has developed an elegant new way to identify the kinds of tasks and occupations likely to be affected by particular AI capabilities—and has graciously shared his "exposure scores" for occupations to allow further analysis by Brookings.[2] In doing so, Webb has allowed us to further test a new analytic approach that is extremely important, as it allows us to probe the kinds of occupations likely to be affected by AI specifically, as opposed to those affected by the broader swath of automation technologies. With these data we are able to rely fully on statistical associations, as opposed to relying in large part on expert prognostications.

What do we find in working with Webb's data? Above all, that Webb's AI measures depict a very different range of impacts on the workforce than those from robotics and software. Where the robotics and software that dominate the automation field seem mostly to involve "routine" or "rule-based" tasks (and thus lower- or middle-pay roles), AI's distinctive capacities suggest that higher-wage occupations will be some of the most exposed.

Unlike robotics (associated with the factory floor) and computers (associated with routine office activities), AI has a distinctly white-collar bent. While earlier waves of automation have led to disruption across the lower half of the wage distribution, AI appears likely to have different impacts, with its own windfalls and challenges. White-collar, well-paid America—radiologists, legal professionals, optometrists, and many more—will likely get no free pass on this flavor of digital disruption.

Given the potential of these technologies, it behooves us to get a clearer read on their labor market reach, which is what the following pages begin to do.

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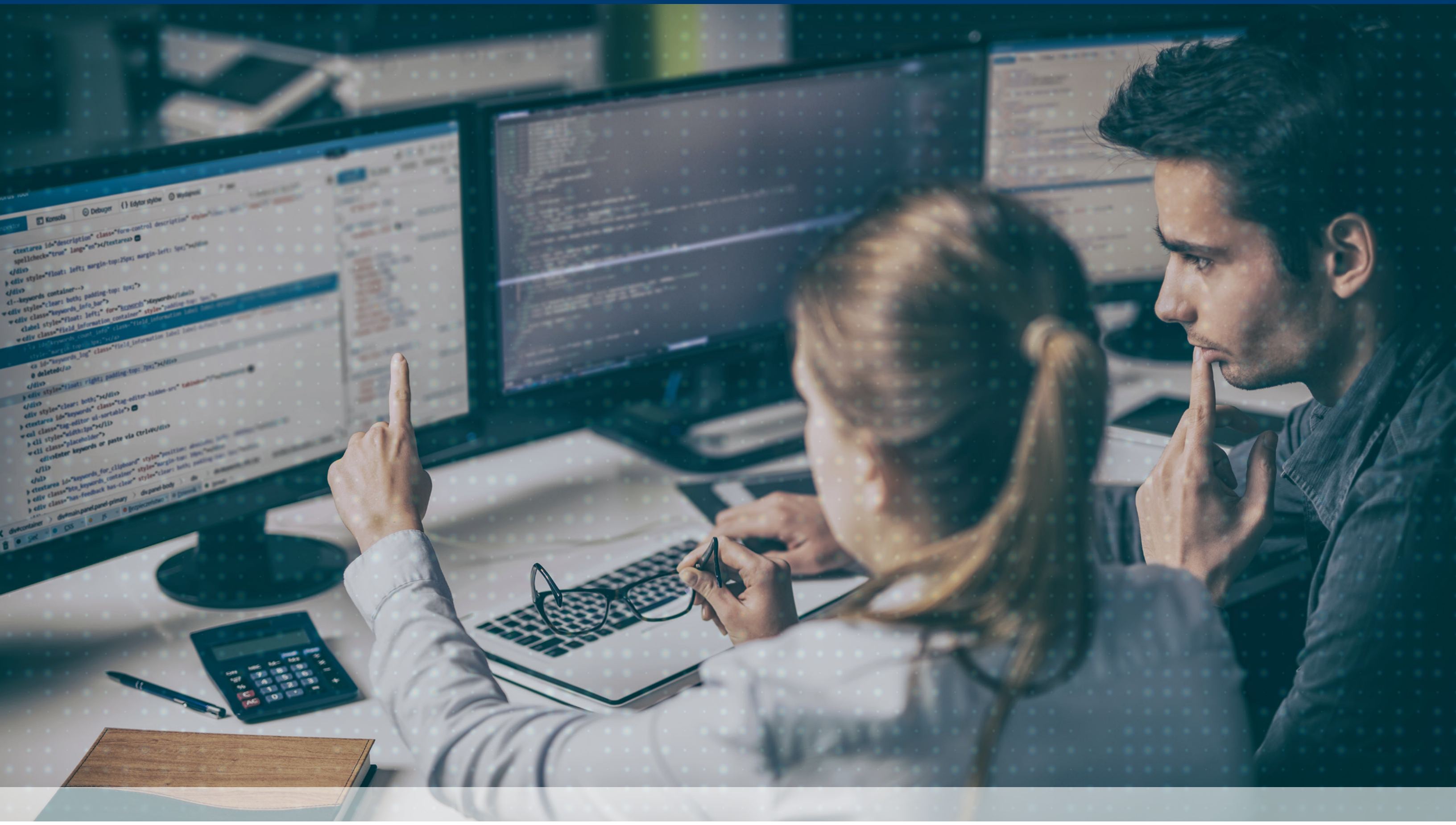


What we know about AI, and what we don't

First, some context: What is AI, and why are its workforce impacts so hard to assess? This is an important question, because the problem of gauging its effects owes to the disparate, changing nature of AI itself, which draws on an ever-evolving set of algorithms and approaches to generating machines with human-level intelligence.

What is AI?

Part of the challenge of analyzing AI in general is that no single definition of the technology serves to pin down its operations and capabilities.[3] It's only somewhat helpful to say that AI involves programming computers to do things which—if done by humans—would be said to require "intelligence," whether it be planning, learning, reasoning, problem-solving, perception, or prediction.[4] The problem here is that "intelligence" has always been defined as whatever it is that humans can do that computers cannot. But since that frontier has been changing rapidly, the definition doesn't limit the field much.

The definitional problem does not disappear even if the aperture is narrowed to focus on machine learning (ML)—the branch of statistics on which most AI currently depends. Machine learning can be straightforwardly defined as computers' use of algorithms to find statistical patterns in massive amounts of data, which can then be used to make predictions. Such statistical pattern-finding has been around for decades, but this field also is evolving rapidly. Recent years have seen a surge in improved algorithms that have been accelerated by advances in computer speed, data collection, and storage, driving an explosion of improved applications including image recognition, voice interpretation, preference prediction, autonomy, and decision support.[5] This explosion of applications is continually changing the nature and boundaries of ML, adding to the difficulty of defining and analyzing AI as a field and set of applications.

Why AI's workplace impacts are hard to assess

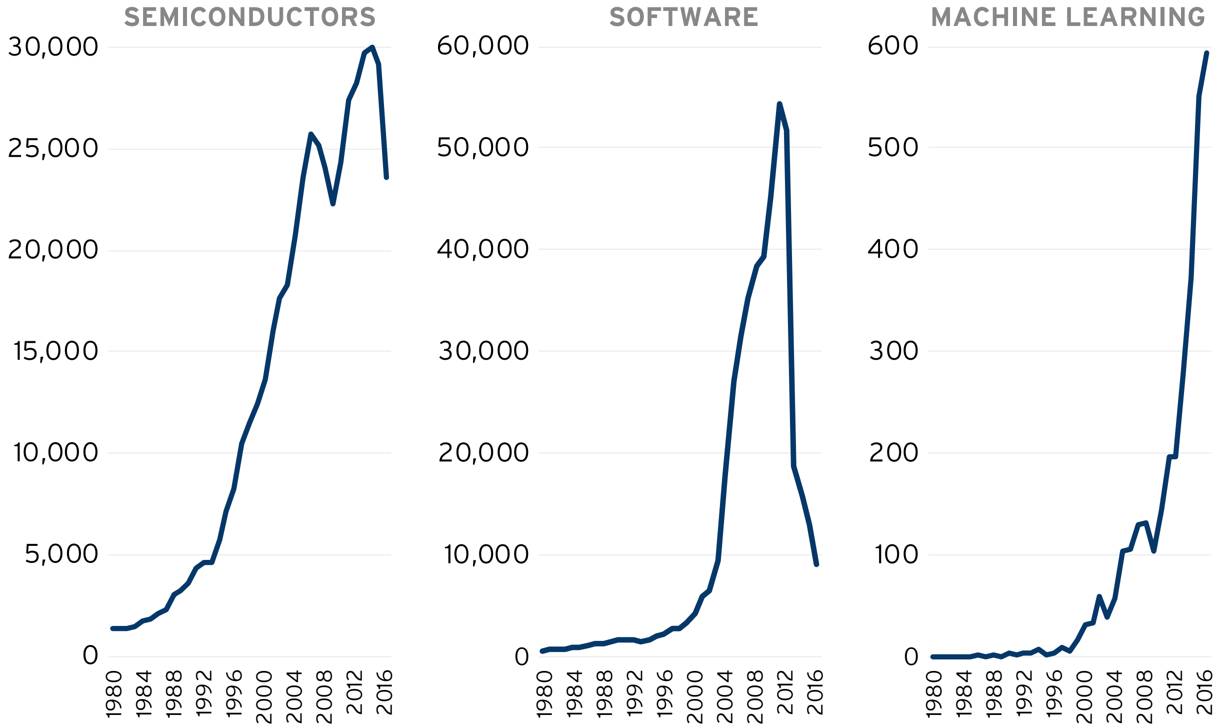
Because AI is such a moving target, efforts to assess its impacts on work are also complicated. Our earlier report on automation explained how assessments of well-recognized technologies—heavily dependent on experts' experience—could be employed to identify the aspects of jobs most susceptible to particular technologies. In that instance, our analyses were made easier by the availability of McKinsey's expert forecasts, which reflected extensive experience with relatively well-established, well-understood robotics and software technologies (several types of AI were included too).

AI presents a more challenging set of issues. Even by reducing the scope of the present analysis to ML applications, analysis of AI on the workforce must contend with a profusion of relatively new, hard-to-discern technologies that have not yet been widely adopted by firms or diffused far across the economy into practical use.

Contrary to robotics and software, for example, researchers have had little time to learn about AI's primary use cases in the economy—as is indicated by Figure 1, which tracks the recent emergence of machine learning patenting.[6]

Figure 1. Index of patent counts by technology

Patent counts by technology, 1980 - 2016



Source: Webb, Short, Bloom, and Lerner (2018) "Some facts of high-tech patenting."

Consequently, as the scholars Erik Brynjolfsson and Tom Mitchell have written, there is "no widely shared agreement on the tasks where machine learning systems excel, and thus little agreement on the expected impacts on the workforce and on the economy more broadly."[7]

Brynjolfsson and Mitchell have done their best to identify AI-suitable tasks (and therefore AI-exposed jobs) using multicriteria subjective rubrics informed by their deep knowledge of the field.[8] However, even they express humility about such efforts. The general takeaway is that the evolving, emergent nature of AI poses a tough challenge for analyses of its impact—especially those that rely on standard expert judgement. Another approach is needed.

Approach: Using AI to assess AI's workforce impacts

This is where Michael Webb's new approach comes in. To circumvent many of the problems posed by AI for labor market analysis, this brief uses the outputs of Webb's novel AI method for quantifying the "exposure" of occupations to assess the broader labor market impacts.

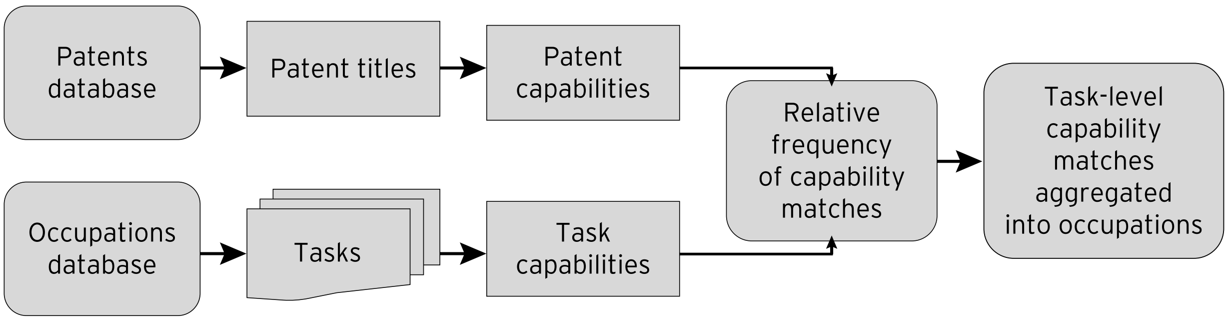
The general approach resembles that of our earlier automation analysis, but draws its special interest from Webb's statistical method for estimating occupations' AI exposure. Those estimates are then employed to evaluate the exposure of U.S. occupational groups, industries, demographic groups, and geographies (the nation as a whole, states, and metropolitan areas).

Webb's exposure estimates are novel because they employ the text of patents to identify the capabilities of AI, and then quantify the extent to which each occupation involves these technologies. (For more on the process see Michael Webb, "The Impact of Artificial Intelligence on the Labor Market" and its appendices.)

Patent texts are useful here because they provide timely predictions of the commercial relevance of specific technological applications. That applicants must pay nontrivial fees for filing them enhances their predictive value. Occupational descriptions are also useful because they provide detailed insight into economic activities at the scale of the whole economy. Studying the two measures' interplay solves a very difficult analytic problem.

This is why Webb uses machine learning in the form of natural language processing to quantify the overlap between patent texts and job description text. The key idea, writes Webb,

Figure 2. Illustration of process for constructing AI exposure measure



Source: Webb (2019)

is that "verb-object pairs, such as 'diagnose-disease,' capture both technological capabilities and economic activities in a transparent, parsimonious way."

Webb first manually identified a pool of 16,400 AI patents containing such keywords as "neural network" in their titles or abstracts. (See Figure 2 nearby). Then, he used an algorithm to extract 8,000 verb-object pairs, such as "diagnose disease" or "recognize aircraft" and tested to see how often those surfaced in the patent titles, which tend to include phrases like "Method for diagnosing diseases" or "Method for recognizing aircraft." Ultimately, Webb produced and ranked a list of frequency information on the appearance of particular jobs in hundreds of AI capabilities, such as the aforementioned "diagnose disease" and "recognize aircraft" as well as phrases such as "predict prognosis" and "generate recommendation."

With these verb-object pairs in hand, Webb then turned to the occupational information contained in the U.S. Department of Labor's O*NET database and located textual overlaps. In O*NET, the work of particular occupations—for example, "doctor"—is broken down into tasks described in free-form text, such as "Interpret tests to diagnose patients' condition." Using that language, Webb was again able to extract the relevant capability pairs (interpret, test; diagnose, condition) from the task description and establish the degree of overlap between specific word-based occupational activities and even brand-new AI capabilities.

That degree of that overlap was converted into a measure of each occupations' "exposure to AI applications in the near future" by weighing each occupational description's degree of overlap with AI patent capabilities, as determined by particular tasks' frequency, importance, and relevance to the job. Finally, these raw exposure scores were normalized with a mean of zero, meaning that the standardized scores presented in our analysis reflect the number of standard deviations above or below the average occupational exposure to AI.

Through this method, Webb has been able to assemble a granular, statistical readout of the specific documented task content of hundreds of occupations that are exposed to emerging real-world AI capabilities. For instance, in the precision agriculture field, Webb's data details the specific statistical extent to which patented AI capabilities (reflected in extracted word pairs such as "develop, grid" or "identify, site" or "test, characteristic") show up in the work descriptions of agricultural technicians, one of which—according to O*NET—calls for a well-paid worker to "Use geospatial technology to develop soil sampling grids or identify sampling sites for testing characteristics such as nitrogen, phosphorus, or potassium content."[9]

Table 1. Top extracted verbs and characteristic nouns of artificial intelligence patents

Verb	Example nouns
recognize	pattern, image, speech, face, voice, automobile, emotion, gesture, disease
predict	quality, time, performance, fault, behavior, traffic, prognosis, treatment
detect	signal, abnormality, defect, object, fraud, event, spammer, human, cancer
identify	object, type, damage, illegality, classification, relationship, importance
determine	state, similarity, relevance, importance, characteristic, strategy, risk
control	process, emission, traffic, engine, robot, turbine, plant, discharging
generate	image, rating, lexicon, warning, description, recommendation
classify	data, object, image, pattern, signal, text, electrogram, speech, motion

Note: Table reflects the top eight verbs by pair frequency for AI patents, and their characteristic direct objects.
Source: Webb (2019)

As to what such potential "exposure" means, it does not signify that AI has already made inroads into the named occupation, or that it will necessarily replace work or jobs once it does. Rather, the exposure measure employed here only suggests that in particular occupations *some kind of impact* can be expected, whether positive or negative.[10] With that said, Webb's work brings an additional degree of disquiet to the automation story. Webb's modeling suggests that just as the impacts of robotics and software tend to be sizable and negative on exposed middle- and low-skill occupations, so AI's inroads are projected to negatively impact higher-skill occupations.

Hence the present analysis. By applying Webb's occupational exposure values to other data on employment and workforce characteristics, we develop an array of employment-weighted and normalized AI-exposure averages for industry groupings, demographic groups, and geographies of interest.

Findings

What do the data show? A number of key points about the labor market impacts of AI come to the fore:

1. AI could affect work in virtually every occupational group

To begin with, AI resembles more generic "automation" in its broad projected reach, as previously measured by Brookings and others. Fully 740 out of the 769 occupational descriptions Michael Webb analyzed contain a capability pair match with AI patent language, meaning at least one or more of its tasks could potentially be exposed to, complemented by, or completed by AI.

Importantly, this does not mean such tasks will be broadly replaced and result in work loss. But the statistical reach of AI capabilities does underscore the technology's wide relevance and potential power. AI, in this respect, almost certainly represents what Bresnahan and Trajtenberg call a "general purpose technology—a technology that becomes pervasive and generates follow-on innovation."[11] As such, it appears poised to have significant impacts across the labor market.

2. Better-paid, white-collar occupations may be most exposed to AI, as well some agriculture and manufacturing positions

Webb's statistics suggest that AI's impacts will not be equally distributed, and that it will have a very different set of impacts than the broader array of automation technologies (dominated by robotics and software) mentioned earlier.

Whereas our and other's work has shown that less-educated, lower-wage workers appear most exposed to potential disruption from robotics and software, Webb's AI exposure estimates and our analyses here suggest the opposite pattern: Better-educated, better-paid workers will be the most affected by the new technology, with some exceptions.

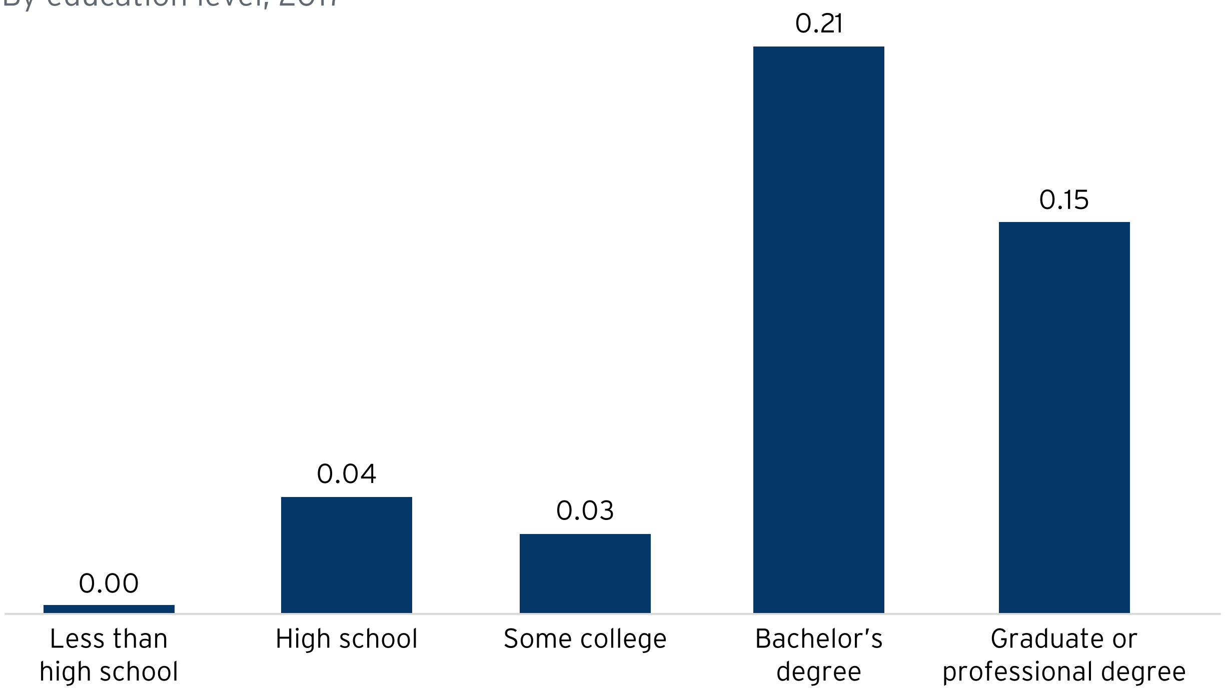
Figures 3 and 4 show what this looks like when AI exposure is plotted first against education levels and, second, across occupations' wage percentiles.

Figure 3 suggests that those with bachelor's degrees will be much more exposed to AI than less-educated groups, and Figure 4 illustrates the parallel finding that workers in higher-wage occupations (toward the right) will be much more exposed than lower-wage workers. The exposure curve peaks at the 90th percentile, suggesting that while middle- and upper-middle-class workers are likely to be impacted by artificial intelligence, the most elite workers—such as CEOs—appear to be somewhat protected.

To dig into this more, Table 2 displays some representative occupations and their associated AI exposures, while Figure 5 breaks all of this out in terms of aggregate shares of the nation's overall employment.

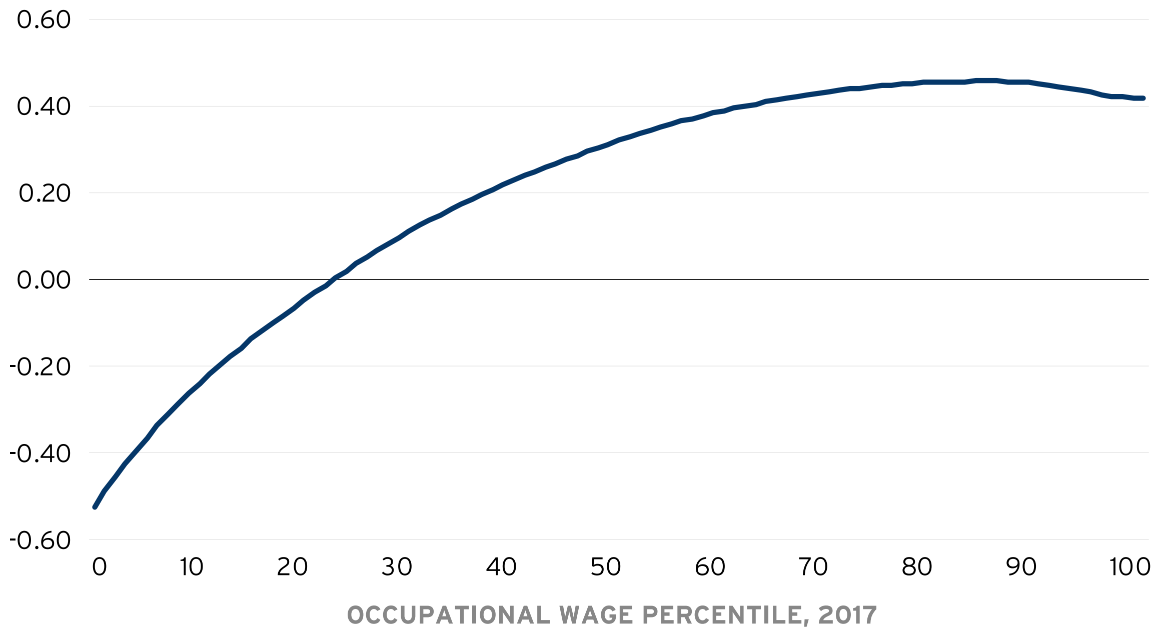
Figure 3. Average standardized AI exposure

By education level, 2017



Source: Brookings analysis of Webb (2019) and IPUMS-USA ACS 1-year microdata

Figure 4. Standardized AI exposure, 2017



Note: Figures smoothed using a LOWESS regression
Source: Brookings analysis of Webb (2019) and OES data

Table 2—which lists a few occupations and their AI exposures and wages—suggests some patterns. A different set of high-exposure occupations stands out than what is found in more conventional automation analyses. At the high end of AI involvement, for example, are numerous well-paid occupations that had relatively low exposure in our earlier, all-encompassing automation analysis. They range from market research analysts and sales managers to programmers, management analysts, and engineers. Often analytic or supervisory, these roles appear heavily involved in pattern-oriented or predictive work, and may therefore be especially susceptible to the data-driven inroads of AI, even though they seemed relatively immune in earlier analyses.

By contrast, it appears that numerous low-paying, rote jobs engaged in providing hands-on services (such as in personal care, food preparation, or health care) will be relatively unexposed to changes from AI applications, at least for now.

The upshot: AI will be a much greater factor in the future work lives of relatively well-paid managers, supervisors, and analysts (as well as production workers, who are increasingly well-educated in many occupations as well as heavily involved with AI on the shop floor). It may be much less of a factor in the work of most lower-paid service workers.

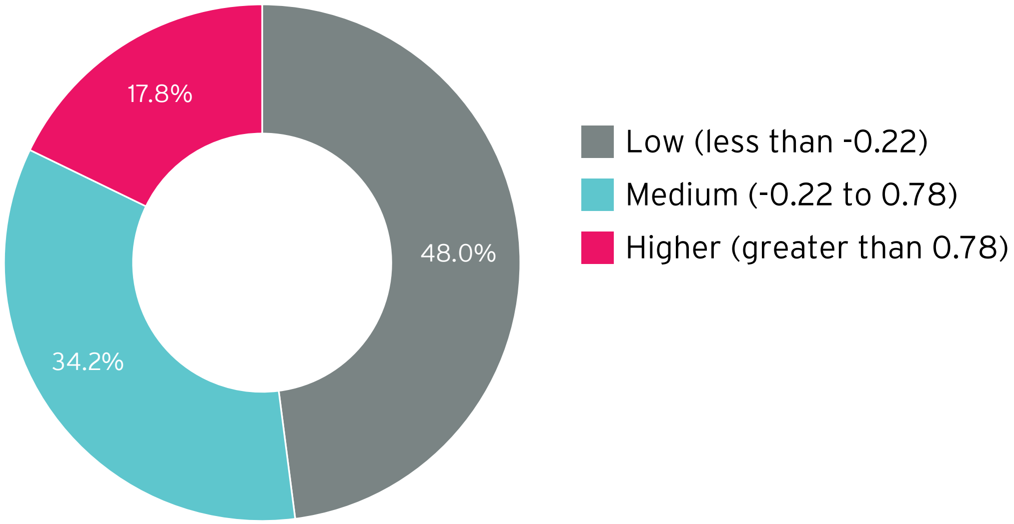
As to how these patterns add up, Figure 5 categorizes the nation's work into tiers of "low," "medium," and "high" job exposure.[12] Notwithstanding the broad, wide-ranging future possibilities of AI, only a relatively small segment of jobs stands to be heavily affected by AI applications given the nature of present technologies and jobs. The generally well-paying analytic or managerial jobs facing "high" exposure add up to only about 18% of U.S. employment (25 million jobs in 2017). By contrast, the aggregate data suggest that a sizable 34% of U.S. employment (48 million

Table 2. Average wages and standardized AI exposure for representative occupations

Occupation	Average wage, 2017	Standardized AI exposure
Market research analysts and marketing specialists	$70,620	3.03
Sales managers	$135,090	2.77
Computer programmers	$85,180	1.96
Personal financial advisors	$124,140	1.33
Management analysts	$91,910	0.73
Dental hygienists	$74,680	0.60
Registered nurses	$72,180	0.44
Plumbers, pipefitters, and steamfitters	$57,070	0.22
Automative service technicians and mechanics	$41,400	0.05
Web developers	$74,110	-0.07
Human resources specialists	$64,890	-0.21
Welders, cutters, solderers, and brazers	$43,410	-0.35
Dental assistants	$37,890	-0.79
Combined food preparation and serving workers	$20,460	-1.01
Cooks, restaurant	$25,430	-1.37
All occupations	**$50,620**	**0.00**

Source: Brookings analysis of Webb (2019) and OES data

Figure 5. Share of jobs by AI exposure, 2017



Source: Brookings analysis of Webb (2019) and OES data

jobs) may experience "medium" exposure to AI, while fully 48% of jobs (67 million of them) will face no or only "low" AI exposure. This seems like a significant yet relatively confined coming disruption.

3. Business-finance-tech industries will be more exposed, as will natural resource and production industries

Turning to industry patterns, the imprint of AI both resembles and differs from that foreseen in our earlier analysis of automation, with its orientation toward robotics and software. As before, the inroads of technology are highest among primary and secondary activities such as manufacturing, agriculture, and resource extraction.

Once again, motor vehicle manufacturing and textile industries display some of the highest average AI exposure scores, which likely reflects the explosion of emergent AI applications in industries for controlling robotics, detecting anomalies, recognizing patterns, and more. Apparel manufacturers can now train AI systems to quickly and accurately identify defective garments on a production line, while carmakers can deploy algorithms to process reams of sensor data and anticipate when equipment failures are likely to occur or when to perform maintenance. The story changes when we assess the service

Table 3. Average standardized AI exposure by industrial sector

Industrial sector	Employment, 2017	Standardized AI exposure
Agriculture, Forestry, Fishing and Hunting	424,020	1.21
Utilities	552,270	0.73
Manufacturing	12,299,590	0.61
Mining, Quarrying, and Oil and Gas Extraction	591,130	0.50
Professional, Scientific, and Technical Services	8,850,270	0.47
Information	2,800,500	0.44
Management of Companies and Enterprises	2,326,030	0.30
Construction	6,903,100	0.28
Administrative and Support and Waste Management and Remediation Services	9,108,240	0.20
Finance and Insurance	5,857,390	0.19
Transportation and Warehousing	5,792,400	0.16
Public Administration	9,661,970	0.11
Wholesale Trade	5,845,600	0.06
Real Estate and Rental and Leasing	2,147,230	-0.07
Health Care and Social Assistance	20,208,050	-0.14
Educational Services	13,042,590	-0.17
Other Services (except Public Administration)	4,141,920	-0.17
Arts, Entertainment, and Recreation	2,370,170	-0.19
Retail Trade	16,009,150	-0.30
Accommodation and Food Services	13,617,690	-0.84
All industries	**142,549,310**	**0.00**

Source: Brookings analysis of Webb (2019) and OES data

sectors' exposure to AI. High-tech digital services such as software publishing and computer system design—that before had low automation susceptibility—exhibit quite high exposure, as AI tools and applications pervade the technology sector. At the same time, sizable, low-wage service industries that were highly vulnerable to more standard automation in earlier analyses now reside among some of the least-exposed industries when it comes to AI. Most notably, accommodation and eating-drinking services (along with retail) now join health and education industries as relatively immune to AI.

It is the smaller, better-paying high-tech or professional industries and their workers that will be most changed by AI. Professional services firms managing procurement, for instance, can use AI systems to optimize the pace of supply orders and eliminate duplicative purchases across departments. Bigger, lower-paying service and care industries appear much less susceptible.

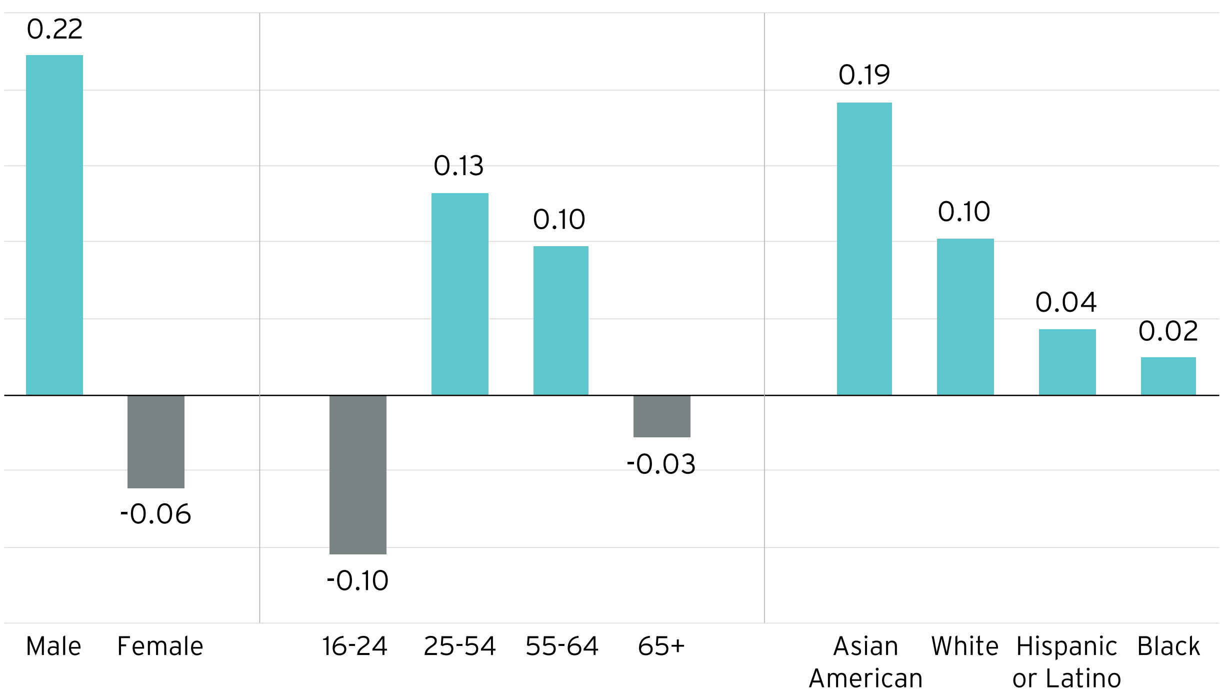
4. AI looks most destined to affect men, prime-age workers, and white and Asian American workers

Consistent with the varying exposure of occupational and industry groups, AI appears likely to impinge on particular demographic groups in disparate ways that differ at key points from the impacts predicted in the previous automation analysis.

Men, with their overrepresentation in both analytic-technical and professional roles (as well as production), work in occupations with much higher AI exposure scores than women.

Figure 6. Average standardized AI exposure

By sex, age, and race-ethnicity; 2017



Note: American Indians and Alaskan Natives, Native Hawaiians and Pacific Islanders, and people indicating they are two or more races are not shown due to limited data availability.
Source: Brookings analysis of Webb (2019) and IPUMS-USA ACS 1-year microdata

Consequently, male workers' aggregate AI exposure exceeds that of any other group. Women's heavy involvement in "interpersonal" education, health care support, and personal care services appears to shelter them. This both tracks with and accentuates the finding from our earlier analysis.

Displaying demographic groups' overrepresentation and underrepresentation in particular occupational groups, aligned with exposure levels, yields the "heat" chart in Table 4.

The most striking patterns involve gender. Women, in the top half of their column, are heavily underrepresented by red and bright red cells covering higher-exposure occupations such as engineering, installation-maintenance, construction, and transportation. At the same time, they are overrepresented by dark blue cells in lower-exposure fields such as health care, education, and personal care. For men, the story is reversed, as they are overrepresented in higher-exposure fields and underrepresented in occupational groups less involved with AI.

Age also matters. "Prime-age" workers aged 25 to 54 are employed in occupations that are going to be disproportionally involved with AI. The exposure pattern here varies sharply from the automation analysis, which found that young workers (ages 16 to 24) faced the highest automation risks given their heavy overrepresentation in low-skill food preparation jobs. In the case of AI, however, exposure scores peak in midcareer. This reflects the greater education and experience requirements for many of the high-tech, analytics, and managerial occupations that are becoming most involved with AI. Midcareer professional and technical

Table 4. Over- and underrepresentation of workers in occupation groups by demographic group

Occupation group	Avg. standardized AI exposure	Women	Men	White	Black	Latino or Hispanic	Asian American
Farming, fishing, and forestry	1.48	-22.8%	22.8%	-23.7%	-8.7%	37.1%	-4.3%
Life, physical, and social sciences	1.19	-0.8%	0.8%	5.3%	-5.6%	-8.1%	8.6%
Computer and math	1.04	-22.3%	22.3%	-0.7%	-4.1%	-9.4%	14.2%
Architecture and engineering	0.86	-32.1%	32.1%	8.2%	-6.2%	-7.8%	6.3%
Production	0.84	-19.4%	19.4%	-6.2%	1.5%	5.5%	-0.2%
Business and financial operations	0.64	8.6%	-8.6%	7.4%	-2.0%	-7.1%	2.2%
Installation, maintenance, and repair	0.46	-43.9%	43.9%	5.6%	-4.2%	1.9%	-3.0%
Construction and extraction	0.39	-44.8%	44.8%	-7.0%	-5.4%	17.1%	-4.6%
Transportation and material moving	0.38	-30.0%	30.0%	-8.4%	5.9%	5.4%	-2.9%
Protective services	0.35	-25.3%	25.3%	-2.5%	8.0%	-2.2%	-3.7%
Arts and entertainment	0.29	-0.1%	0.1%	10.3%	-4.2%	-6.1%	-0.1%
Healthcare practitioners	0.26	27.9%	-27.9%	5.8%	-0.6%	-8.3%	3.5%
Management	0.25	-6.2%	6.2%	10.8%	-4.1%	-6.3%	0.3%
Legal	0.14	6.9%	-6.9%	14.6%	-5.1%	-7.5%	-1.4%
Community and social services	-0.25	18.1%	-18.1%	-0.1%	6.0%	-4.1%	-2.3%
Office and administrative support	-0.34	22.8%	-22.8%	0.1%	1.9%	-0.7%	-1.4%
Education	-0.37	25.4%	-25.4%	9.2%	-2.1%	-6.0%	-0.8%
Building and grounds cleaning	-0.45	-10.4%	10.4%	-17.9%	3.4%	17.1%	-2.7%
Healthcare support	-0.45	38.6%	-38.6%	-14.9%	13.2%	1.7%	-0.7%
Sales	-0.47	2.5%	-2.5%	2.5%	-1.0%	-1.0%	-0.7%
Personal care services	-0.62	27.7%	-27.7%	-9.4%	3.8%	0.8%	3.8%
Food preparation and service	-0.92	5.7%	-5.7%	-10.2%	0.7%	8.0%	0.2%
Share of total employment	**0.00**	**47.9%**	**52.1%**	**62.4%**	**11.7%**	**16.5%**	**6.1%**

Note: Red indicates under- and blue overrepresentation. Shading indicates magnitude of difference from group's share of total employment. American Indians and Alaskan Natives, Native Hawaiians and Pacific Islanders, and people indicating they are two or more races are not shown due to limited data availability.
Source: Brookings analysis of Webb (2019) and IPUMS-USA ACS 1-year microdata

workers will likely be at the forefront of dealing with AI.

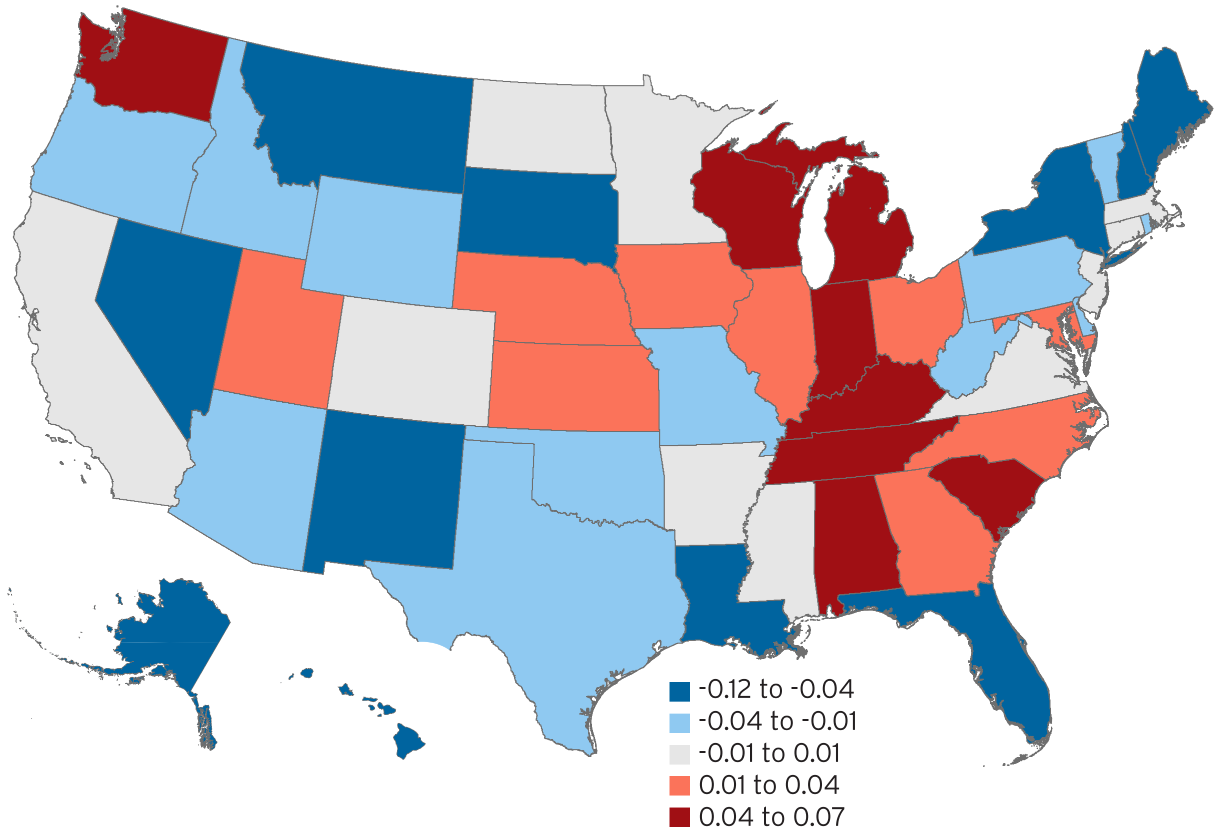
Similarly inverse to the earlier automation findings that focused on robotics and software are the AI results for racial and ethnic groups. Now, it is white and Asian American workers especially who appear most exposed to workplace technology change. White and Asian American workers' heavy overrepresentation in technology, engineering, and legal-managerial occupations ensures both groups will be impacted most by the arrival of AI. Conversely, AI is less likely to affect Black and Latino or Hispanic workers given their overrepresentation in occupations such as personal care work, facilities maintenance, and community and social services occupations—all of which we project to have low AI exposure in the coming years.

5. Bigger, higher-tech metro areas and communities heavily involved in manufacturing are likely to experience the most AI-related disruption

Turning to the geography of AI, further analysis shows that while AI will be employed virtually everywhere, its inroads will vary across space—determined by the local industry, education, and occupational mix.

An initial look at the state-level exposure map suggests that the nation's eastern heartland—sweeping from **Wisconsin** and **Michigan** though **Indiana**, **Kentucky**, and into **Alabama** and **Georgia**—will be heavily involved with AI given its association with manufacturing, which is increasingly linked with machine learning and

Map 1. Average standardized AI exposure by state, 2017



Source: Brookings analysis of Webb (2019) and OES data

related applications. At the same time, significant additional exposure can be discerned along the high-tech and managerial **Boston-Washington, D.C.** corridor as well as in **Washington** state and **California**.

Much of this map is familiar to earlier mappings of automation's impact, with two exceptions. **Nevada** has flipped from being one of the most exposed states to one of the least, since AI is much less likely to disrupt the accommodation and food services sectors. Conversely, **Washington** state has moved in the other direction and is highly exposed to AI, which surely has to do with its specializations in both advanced manufacturing and technology in and around Seattle.

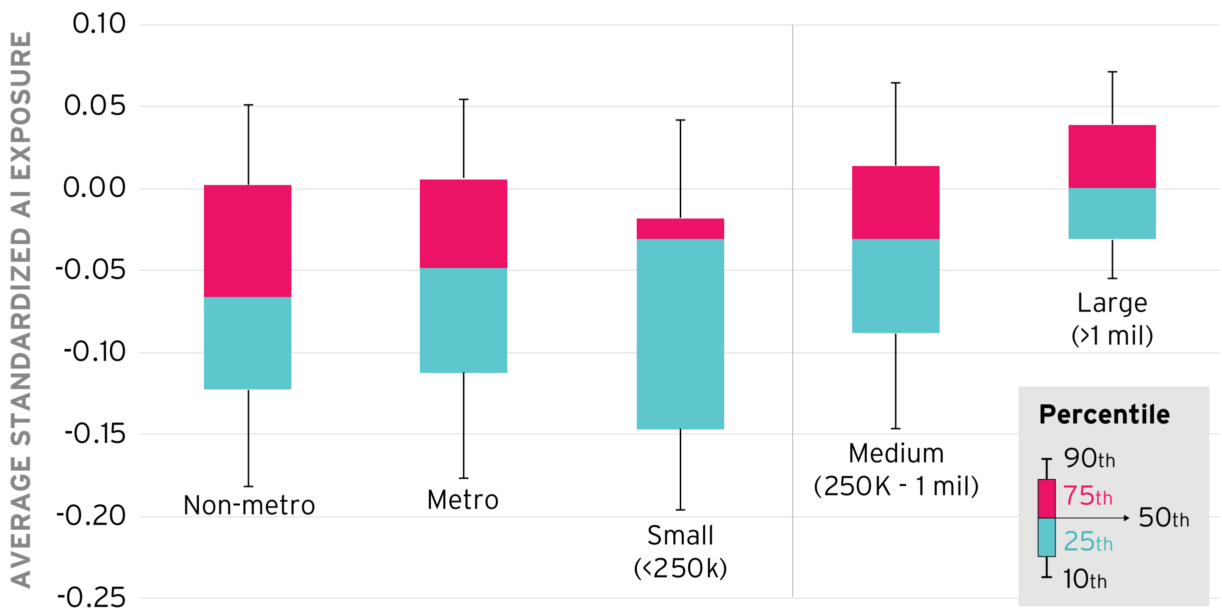
More reversals surface when looking at community types. Contrary to the automation maps, the present AI analysis reveals that smaller, more rural communities are significantly less exposed to technological disruption than larger, dense urban ones. This likely reflects the basic urban geography of the information, technology, and professional-managerial economy, with its orientation toward analytics, prediction, and strategy—all susceptible to AI solutions.

Similarly, bigger, tech-focused metro areas and manufacturing hubs dominate the list of highly exposed larger places, and the full list of exposed metro areas displays a number of smaller manufacturing or agricultural places as well.

Among the most AI-exposed large metro areas are **San Jose, Calif.**, **Seattle**, **Salt Lake City**, and **Ogden, Utah**—all high-tech centers—along with agriculture and logistics hub **Bakersfield, Calif.** and manufacturing centers **Greenville, S.C.**, **Detroit**, and **Louisville, Ky**. Filling out the high-exposure end of the full list are manufacturing places (**Elkhart-Goshen, Ind.**, **Dalton, Ga.**, and **Columbus, Ind.**), agricultural centers such as **Madera** and **Salinas, Calif.**, and high-tech concentrations including **Boulder, Colo.** and **Huntsville, Ala**.

Figure 7. Distribution of average standardized AI exposure

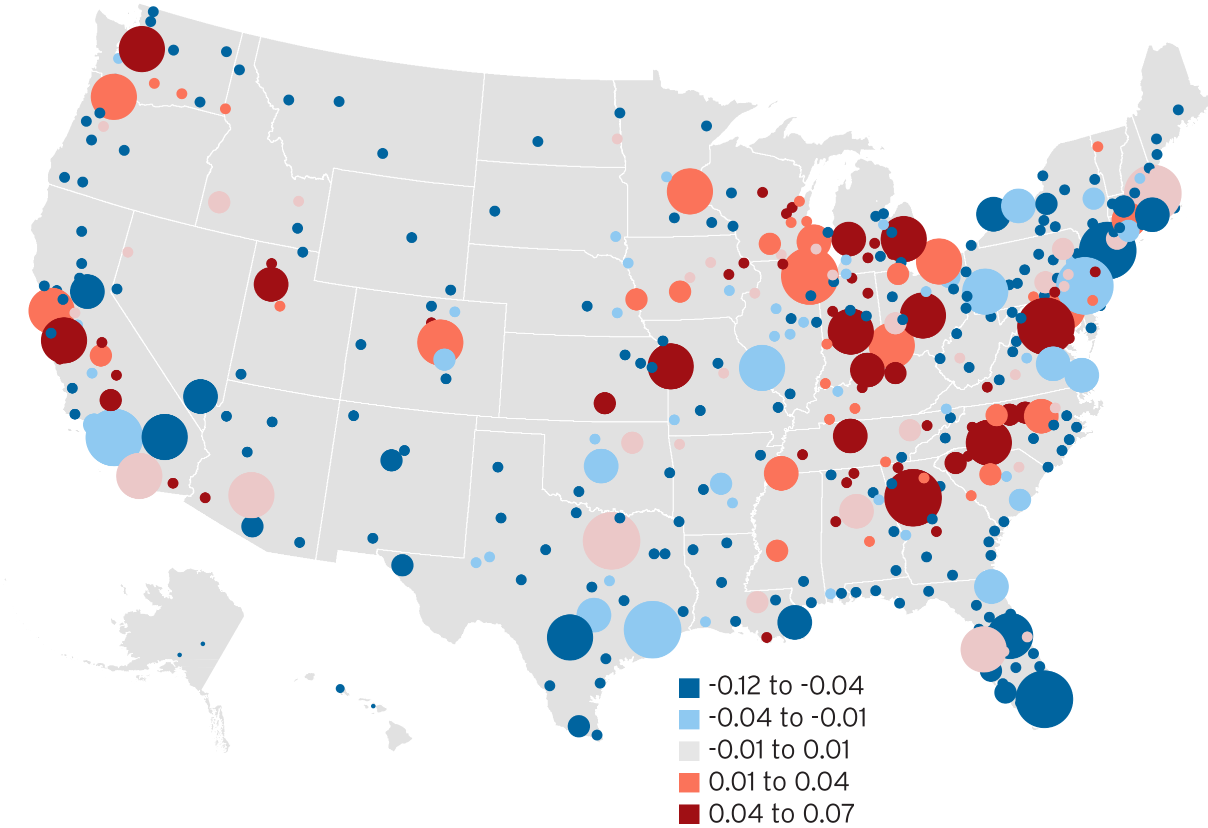
By community size type, 2017



Source: Brookings analysis of Webb (2019) and OES data

Places that appear most disconnected from AI are heavily concentrated in the Sun Belt. They range from bigger, service-oriented metro areas such as **El Paso, Texas**, **Las Vegas**, and **Daytona Beach, Fla.**, to smaller, "leisure" communities including **Hilton Head** and **Myrtle Beach, S.C.** and **Ocean City, N.J.** These metro areas lie far from manufacturing and technical-managerial regions, and focus on providing low-tech, AI-free interpersonal services to the leisure class.

Map 2. Average standardized AI exposure by metro area or NECTA, 2017



Note: Dot size reflects 2017 metro and NECTA population.
Source: Brookings analysis of Webb (2019) and OES data

Table 5. Top 15 and bottom 5 metro areas and NECTAs by average standardized AI exposure, 2017

Rank	Name	Avg. standardized AI exposure
1	San Jose-Sunnyvale-Santa Clara, CA	0.20
2	Bakersfield, CA	0.19
3	Greenville-Anderson-Mauldin, SC	0.14
4	Grand Rapids-Wyoming, MI	0.11
5	Seattle-Tacoma-Bellevue, WA	0.10
6	Detroit-Warren-Dearborn, MI	0.10
7	Louisville/Jefferson County, KY-IN	0.08
8	Salt Lake City, UT	0.08
9	Greensboro-High Point, NC	0.07
10	Ogden-Clearfield, UT	0.06
11	Nashville-Davidson--Murfreesboro--Franklin, TN	0.05
12	Durham-Chapel Hill, NC	0.05
13	Indianapolis-Carmel-Anderson, IN	0.05
14	Atlanta-Sandy Springs-Roswell, GA	0.05
15	Charlotte-Concord-Gastonia, NC-SC	0.05
...	...	...
96	El Paso, TX	-0.14
97	Cape Coral-Fort Myers, FL	-0.15
98	Las Vegas-Henderson-Paradise, NV	-0.16
99	Deltona-Daytona Beach-Ormond Beach, FL	-0.17
100	McAllen-Edinburg-Mission, TX	-0.24

Note: Only include top 100 largest metros/NECTAs.
Source: Brookings analysis of Webb (2019) and OES data

Discussion

These new statistics suggest that the spread of AI will not just amount to "more of the same," and that the onset of AI will introduce new riddles into speculation about the future of work.

Given their difference from previous analyses purporting to discuss AI, Michael Webb's novel procedures demonstrate that we have a lot to learn about artificial intelligence, and that these are extremely early days in our inquiries. What's coming may not resemble what we have been experiencing or expect to experience.

Webb's machine learning statistics suggest AI could bring new patterns of impact across the labor market—ones fundamentally different from those brought by previous technologies.

It's clear that past automation analyses—including our own, with its amalgamation of robotics, software, and artificial intelligence—have likely obscured AI's distinctive impact. Based on expert familiarity, previous analyses have almost certainly been dominated by the ways robotics and software have been able to take over numerous routine, highly structured, and repetitive tasks.[13]

These analyses have tended to suggest that automation's main effects will be to displace work across the middle of the skill and wage spectrum (such as factory workers and office clerks) while leaving the status quo more or less intact for both high-pay and low-pay interpersonal or nonroutine work (such as chemical engineers and home health aides, respectively).

However, the more refined empirical research presented here suggests that AI's ability to employ statistics and learning to carry out nonroutine work means that these technologies are set to affect very different parts of the workforce than previous automation. Most strikingly, it now looks as if whole new classes of well-paid, white-collar workers (who have been less touched by earlier waves of automation) will be the ones most affected by AI.

Given that, society should get ready for very different patterns of impact than those that accompanied the broad adoption of robotics and software. While the last waves of automation led to increases of inequality and wage polarization, it's not clear that AI will have the same effects.[14]

The complex interplay of task substitution, task complementarity, and the creation of new work driven by increased productivity and consumer demand makes it hard to play out exact labor market impacts.[15] Consequently, this brief quantifies only the *potential exposure* of occupations to AI—not *whether* adoption has occurred or *how* it will affect that work. While the present assessment predicts areas of work in which *some kind of impact* can be expected, it does not speak to whether those areas will actually adopt AI, or what sorts of impacts—positive or negative—may occur (although Webb's work recalls the precedents of robotics and software to suggest likely job losses).[16]

And yet it is possible to play out the kinds of impacts AI may bring. For example, Brynjolfsson and Mitchell and Agrawal and others—who define machine learning as a "prediction" technology—provide helpful reviews of real-world use cases that begin to tease out the disparate ways AI might interact with human work. Agrawal and his colleagues employ a standard framework in the literature to conclude that AI might alternatively *substitute* capital for labor in many prediction tasks, *complement* labor by automating other prediction work, or *create new work*.[17] Agrawal's discussion—supplemented by Brynjolfsson and Mitchell's—points out some of the crosscutting dynamics that surround AI's potential employment impacts.[18]

In this vein, the **substitution** of AI for some well-paid human prediction work is a certainty. All kinds of demand forecasting within companies are increasingly being replaced by AI, as are office and phone workers, transcription and translation workers, customer service workers, credit monitors, and financial analysts.[19] Many parts of the human resources workflow—such as recruiting—are being broken down into prediction tasks so that they can be performed by AI applications. Similarly, a number of artificial intelligence applications are substituting technology for labor in the legal field by automating scanning and prediction tasks. While lawyers may still make the ultimate decisions, lower-level researchers and paralegals may see their ranks dwindle as AI saves firms time and improves accuracy. And yet, while the net substitution of AI for some legal work seems likely, improved speed, volume, and accuracy could expand the industry enough to offset some of the aggregate employment losses.[20]

At the same time, both Brynjolfsson and Mitchell as well as Agrawal and colleagues report other, more encouraging ways AI is beginning to affect white-collar employment. One is the **complementarity** that results when AI enhances labor by automating constituent tasks of jobs in ways that improve human decisionmaking and productivity. Agrawal and his coauthors relate how a company called Atomwise is using AI to help its drug industry partners predict which molecules have the most potential for further exploration, subsequently increasing the demand for real-world experiments performed by humans.[21] Agrawal and company add that even in the case of radiology—where machine scan reading can meet or even surpass human diagnostic accuracy—image recognition affects just two of the 29 tasks O*NET associates with the radiologist occupation. Given this, it's not obvious that the number of radiologists will fall; it might even rise as radiologists are able to spend more time consulting with other physicians about optimal diagnoses and treatment strategies, thus expanding their role in the overall treatment system.[22]

Finally, there are ways that AI might create entirely **new work** for humans. Some such new work is easy to predict: Today's legions of machine learning engineers and research scientists—not to mention AI solutions architects, sales engineers, and consultants—will undoubtedly proliferate. This growth, meanwhile, may be exceeded by the growth of a very different and less fortunate group of workers—those who manually label data to train AI algorithms.[23] Then, there is the new work that is indirectly created. Just as the automobile created jobs not only in auto manufacturing plants but also in pumping stations, roadside restaurants, and the new suburban America that emerged, it seems likely that AI will have similarly far-reaching—if difficult to predict—indirect effects.

In sum, while the statistics now emerging on AI's job market locus point to particular areas of impact, it is clear that much more study of particular ML and AI use cases will be necessary to understand their precise implications for specific tasks and jobs.[24]

For now, we can draw two conclusions:

First, AI is a very different technology than earlier types of automation, and is going to most affect a very different part of the workforce.

Second, because even less is known about AI than other types of automation, it appears much more ambiguous and confined in its impacts, at least for now.

Much more inquiry—qualitative and empirical—is needed to tease out AI's special genius.

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Endnotes

1. See Chris Meserole, "What Is Machine Learning?" (Washington: Brookings Institution, 2018).

2. Michael Webb, "The Impact of Artificial Intelligence on the Labor Market" Working paper. September, 2018.

3. Shukla Shubhendu and Jaiswal Vijay, "Applicability of Artificial Intelligence in Different Fields of Life." *International Journal of Scientific Engineering and Research* 1 (1): 2347-3678.

4. *Ibid*. Shubhendu and Vijay note that John McCarthy, one of the founders of AI research, once defined the field as "getting a computer to do things which, when done by people, are said to involve intelligence." See also Darrell M. West, "What is artificial intelligence?" (Washington: Brookings Institution, 2018).

5. For more on how the emergence of new tools and techniques for analyzing are opening up new sorts of AI solutions in business and economic analysis see Hal R. Varian, "Big Data: New Tricks for Econometrics." *Journal of Economic Perspectives* 28 (2): 3-28.

6. For instance, experts on digital technologies have a pretty good feel for the major applications of "traditional" software (e.g., tracking a company's finances, airline reservation systems) because they arose in the 1970s. By contrast, the fact that half of all AI patents have been published in just the last five years means that there are few formal definitions, few formalized classification or measurement rubrics, few dedicated industry bodies, and few large networks of professional practitioners. See authors' correspondence with Michael Webb, August 22, 2019 and WIPO, "World Technology Trends 2019: Artificial Intelligence." (Geneva, 2019). Webb notes that circumstances are better for researchers looking at both robotics and software. The long-standing nature of the robotics field ensures that there is a well-established industry body (the International Federation of Robotics) and formal classification systems for robots, such a formal standardization of definitions and capabilities from the International Organization for Standardization (ISO). The U.S. Patent and Trademark Office provides a robust classification scheme. For software, the government includes very fine-grained details of software investment in the national accounts.

7. Erik Brynjolfsson and Tom Mitchell, "What Can Machine Learning Do? Workforce Implications." *Science* 358 (6370): 1530-1534.

8. Ibid. See, also, Erik Brynjolfsson, Tom Mitchell, and Daniel Rock, "Economic Consequences of Artificial Intelligence and Robotics: What Can Machines Learn and What Does It Mean for Occupations and the Economy?" *AEA Papers and Proceedings* 108: 43-47.

9. Webb, "The Impact of Artificial Intelligence on the Labor Market."

10. See Webb, "The Impact of Artificial Intelligence on the Labor Market" and Brynjolfsson and Mitchell, "What Can Machine Learning Do?"

11. Timothy F. Bresnahan and Manuel Trajtenberg, "General Purpose Technologies `Engines of Growth?'" *Journal of Econometrics* 65: 83-108.

12. The segmentation into "low," "medium," and "high" exposure levels follows that our previous procedure as discussed in Muro and others, "Automation and Artificial Intelligence: How Machines Are Affecting People and Places" (2019). As we note there, these cutoffs—which run through the automation literature—remain quite arbitrary. To adapt our original cutoffs, we found the occupational percentiles at which 30% and 70% occur in McKinsey's automation exposure data, and used those to identify the comparable normalized AI exposure scores in Webb's data.

The result was a low-to-medium threshold of -0.22 and a medium-to-high threshold of 0.78.

13. Brynjolfsson and Mitchell, "What Can Machine Learning Do?"

14. Ibid. See also Mark Muro and others, "Automation and Artificial Intelligence."

15. For important frameworks for the study of the implications of automation and AI on the demand for labor, wages, and employment see Daron Acemoglu and Pascual Restrepo, "Artificial Intelligence, Automation, and Work." NBER Working Paper 24196 and Ajay Agrawal and others, "Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction." Working paper 25619.

16. See Webb, "The Impact of Artificial Intelligence on the Labor Market" and Brynjolfsson and Mitchell, "What Can Machine Learning Do?"

17. Agrawal and his coauthors base their discussion on their study of dozens of seed-stage companies at the University of Toronto's Creative Destruction Lab accelerator. See Agrawal and others, "Artificial Intelligence."

18. Brynjolfsson and Mitchell, "What Can Machine Learning Do?"

19. Ibid.

20. Ibid.

21. Ibid.

22. Ibid. as well as Thomas H. Davenport and Keith J. Dreyer, "AI Will Change Radiology, but It Won't Replace Radiologists." *Harvard Business Review*. March 27, 2018.

23. Mary L. Gray, Siddharth Suri, *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*. (Boston: Houghton Mifflin Harcourt, 2019).

24. Brynjolfsson and Mitchell, "What Can Machine Learning Do?"

Appendix

Table A1. Occupation groups

SOC code	Name	Average standardized AI exposure score, 2017
45-0000	Farming, fishing, and forestry	1.48
19-0000	Life, physical, and social sciences	1.19
15-0000	Computer and math	1.04
17-0000	Architecture and engineering	0.86
51-0000	Production	0.84
13-0000	Business and financial operations	0.64
49-0000	Installation, maintenance, and repair	0.46
47-0000	Construction and extraction	0.39
53-0000	Transportation and material moving	0.38
33-0000	Protective services	0.35
27-0000	Arts and entertainment	0.29
29-0000	Healthcare practitioners	0.26
11-0000	Management	0.25
23-0000	Legal	0.14
21-0000	Community and social services	-0.25
43-0000	Office and administrative support	-0.34
25-0000	Education	-0.37
37-0000	Building and grounds cleaning	-0.45
31-0000	Healthcare support	-0.45
41-0000	Sales	-0.47
39-0000	Personal care services	-0.62
35-0000	Food preparation and service	-0.92

Source: Brookings analysis of Webb (2019)

Table A2. States

Rank	State	Average standardized AI exposure score, 2017
1	Indiana	0.07
2	Kentucky	0.06
3	Michigan	0.05
4	District of Columbia	0.05
5	Washington	0.05
6	Wisconsin	0.05
7	South Carolina	0.04
8	Tennessee	0.04
9	Alabama	0.04
10	Georgia	0.04
11	Illinois	0.03
12	Utah	0.03
13	Iowa	0.02
14	Maryland	0.02
15	Ohio	0.02
16	Kansas	0.02
17	Nebraska	0.02
18	North Carolina	0.01
19	Connecticut	0.01
20	New Jersey	0.01
21	Minnesota	0.00
22	Virginia	0.00
23	California	0.00
24	Mississippi	0.00
25	Massachusetts	0.00
26	Colorado	0.00
27	North Dakota	0.00
28	Arkansas	-0.01
29	Arizona	-0.01
30	Pennsylvania	-0.01
31	Vermont	-0.01
32	Oregon	-0.02
33	Idaho	-0.02
34	Missouri	-0.02

35	Wyoming	-0.02
36	Oklahoma	-0.02
37	Rhode Island	-0.03
38	West Virginia	-0.03
39	Delaware	-0.04
40	Texas	-0.04
41	New Hampshire	-0.04
42	Alaska	-0.04
43	Louisiana	-0.04
44	Florida	-0.05
45	South Dakota	-0.06
46	New York	-0.07
47	Maine	-0.07
48	New Mexico	-0.08
49	Montana	-0.09
50	Nevada	-0.11
51	Hawaii	-0.12

Source: Brookings analysis of Webb (2019)

Table A3. Top 100 metro areas

Rank	MSA or NECTA	Average standardized AI exposure score, 2017
1	San Jose-Sunnyvale-Santa Clara, CA	0.20
2	Bakersfield, CA	0.19
3	Greenville-Anderson-Mauldin, SC	0.14
4	Grand Rapids-Wyoming, MI	0.11
5	Seattle-Tacoma-Bellevue, WA	0.10
6	Detroit-Warren-Dearborn, MI	0.10
7	Louisville/Jefferson County, KY-IN	0.08
8	Salt Lake City, UT	0.08
9	Greensboro-High Point, NC	0.07
10	Ogden-Clearfield, UT	0.06
11	Nashville-Davidson--Murfreesboro--Franklin, TN	0.05
12	Durham-Chapel Hill, NC	0.05
13	Indianapolis-Carmel-Anderson, IN	0.05
14	Atlanta-Sandy Springs-Roswell, GA	0.05
15	Charlotte-Concord-Gastonia, NC-SC	0.05
16	Kansas City, MO-KS	0.05
17	Columbus, OH	0.04
18	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.04
19	Wichita, KS	0.04
20	Milwaukee-Waukesha-West Allis, WI	0.04
21	Fresno, CA	0.04
22	San Francisco-Oakland-Hayward, CA	0.04
23	Burlington-South Burlington, VT	0.04
24	Hartford-West Hartford-East Hartford, CT	0.03
25	Columbia, SC	0.03
26	Winston-Salem, NC	0.03
27	Chattanooga, TN-GA	0.03
28	Minneapolis-St. Paul-Bloomington, MN-WI	0.03
29	Chicago-Naperville-Elgin, IL-IN-WI	0.03
30	Portland-Vancouver-Hillsboro, OR-WA	0.03
31	Denver-Aurora-Lakewood, CO	0.03

32	Toledo, OH	0.03
33	Omaha-Council Bluffs, NE-IA	0.02
34	Augusta-Richmond County, GA-SC	0.02
35	Baltimore-Columbia-Towson, MD	0.02
36	Memphis, TN-MS-AR	0.02
37	Madison, WI	0.02
38	Cleveland-Elyria, OH	0.02
39	Raleigh, NC	0.02
40	Provo-Orem, UT	0.02
41	Jackson, MS	0.01
42	Des Moines-West Des Moines, IA	0.01
43	Cincinnati, OH-KY-IN	0.01
44	Boston-Cambridge-Nashua, MA-NH	0.01
45	Dayton, OH	0.01
46	Harrisburg-Carlisle, PA	0.01
47	Phoenix-Mesa-Scottsdale, AZ	0.01
48	Birmingham-Hoover, AL	0.00
49	Stockton-Lodi, CA	0.00
50	Tulsa, OK	0.00
51	Palm Bay-Melbourne-Titusville, FL	0.00
52	Bridgeport-Stamford-Norwalk, CT	0.00
53	Dallas-Fort Worth-Arlington, TX	0.00
54	Baton Rouge, LA	0.00
55	Knoxville, TN	0.00
56	Tampa-St. Petersburg-Clearwater, FL	0.00
57	Boise City, ID	-0.01
58	Lakeland-Winter Haven, FL	-0.01
59	San Diego-Carlsbad, CA	-0.01
60	Charleston-North Charleston, SC	-0.01
61	Oxnard-Thousand Oaks-Ventura, CA	-0.01
62	Pittsburgh, PA	-0.01
63	St. Louis, MO-IL	-0.02
64	Rochester, NY	-0.02
65	Oklahoma City, OK	-0.02
66	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.02

67	Richmond, VA	-0.02
68	Jacksonville, FL	-0.03
69	Little Rock-North Little Rock-Conway, AR	-0.03
70	Houston-The Woodlands-Sugar Land, TX	-0.03
71	Allentown-Bethlehem-Easton, PA-NJ	-0.03
72	Austin-Round Rock, TX	-0.03
73	Worcester, MA-CT	-0.03
74	Virginia Beach-Norfolk-Newport News, VA-NC	-0.03
75	Los Angeles-Long Beach-Anaheim, CA	-0.03
76	Akron, OH	-0.04
77	Albany-Schenectady-Troy, NY	-0.04
78	Colorado Springs, CO	-0.04
79	New Haven, CT	-0.04
80	Sacramento--Roseville--Arden-Arcade, CA	-0.05
81	New York-Newark-Jersey City, NY-NJ-PA	-0.05
82	Miami-Fort Lauderdale-West Palm Beach, FL	-0.05
83	Tucson, AZ	-0.05
84	Spokane-Spokane Valley, WA	-0.05
85	Providence-Warwick, RI-MA	-0.05
86	New Orleans-Metairie, LA	-0.05
87	Syracuse, NY	-0.06
88	Riverside-San Bernardino-Ontario, CA	-0.07
89	Buffalo-Cheektowaga-Niagara Falls, NY	-0.07
90	San Antonio-New Braunfels, TX	-0.08
91	Urban Honolulu, HI	-0.08
92	Orlando-Kissimmee-Sanford, FL	-0.09
93	Albuquerque, NM	-0.09
94	Springfield, MA-CT	-0.10
95	North Port-Sarasota-Bradenton, FL	-0.10
96	El Paso, TX	-0.14
97	Cape Coral-Fort Myers, FL	-0.15
98	Las Vegas-Henderson-Paradise, NV	-0.16
99	Deltona-Daytona Beach-Ormond Beach, FL	-0.17
100	McAllen-Edinburg-Mission, TX	-0.24

Source: Brookings analysis of Webb (2019)

Table A4. All metro areas

Rank	MSA or NECTA	Average standardized AI exposure score, 2017
1	Elkhart-Goshen, IN	0.43
2	Dalton, GA	0.36
3	Madera, CA	0.20
4	San Jose-Sunnyvale-Santa Clara, CA	0.20
5	Spartanburg, SC	0.20
6	Bakersfield, CA	0.19
7	Salinas, CA	0.19
8	Visalia-Porterville, CA	0.19
9	Columbus, IN	0.18
10	Yuma, AZ	0.15
11	Greenville-Anderson-Mauldin, SC	0.14
12	Huntsville, AL	0.13
13	Oshkosh-Neenah, WI	0.13
14	Boulder, CO	0.13
15	Lexington-Fayette, KY	0.13
16	Hickory-Lenoir-Morganton, NC	0.11
17	Grand Rapids-Wyoming, MI	0.11
18	Seattle-Tacoma-Bellevue, WA	0.10
19	Rockford, IL	0.10
20	Lafayette-West Lafayette, IN	0.10
21	Detroit-Warren-Dearborn, MI	0.10
22	Appleton, WI	0.10
23	California-Lexington Park, MD	0.09
24	Battle Creek, MI	0.09
25	Trenton, NJ	0.09
26	Morristown, TN	0.08
27	Louisville/Jefferson County, KY-IN	0.08
28	Wausau, WI	0.08
29	Salt Lake City, UT	0.08
30	Lansing-East Lansing, MI	0.07
31	Tuscaloosa, AL	0.07
32	Ann Arbor, MI	0.07
33	Decatur, AL	0.07
34	Greensboro-High Point, NC	0.07

35	Warner Robins, GA	0.06
36	York-Hanover, PA	0.06
37	Cedar Rapids, IA	0.06
38	Elizabethtown-Fort Knox, KY	0.06
39	Ogden-Clearfield, UT	0.06
40	Houma-Thibodaux, LA	0.05
41	Nashville-Davidson--Murfreesboro--Franklin, TN	0.05
42	Durham-Chapel Hill, NC	0.05
43	Indianapolis-Carmel-Anderson, IN	0.05
44	Fort Wayne, IN	0.05
45	Atlanta-Sandy Springs-Roswell, GA	0.05
46	El Centro, CA	0.05
47	Charlotte-Concord-Gastonia, NC-SC	0.05
48	Dubuque, IA	0.05
49	Kansas City, MO-KS	0.05
50	Blacksburg-Christiansburg-Radford, VA	0.04
51	Merced, CA	0.04
52	Columbus, OH	0.04
53	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.04
54	Wichita, KS	0.04
55	Jackson, TN	0.04
56	Montgomery, AL	0.04
57	Milwaukee-Waukesha-West Allis, WI	0.04
58	Fresno, CA	0.04
59	San Francisco-Oakland-Hayward, CA	0.04
60	Sheboygan, WI	0.04
61	Burlington-South Burlington, VT	0.04
62	Hartford-West Hartford-East Hartford, CT	0.03
63	Lewiston, ID-WA	0.03
64	Green Bay, WI	0.03
65	Columbia, SC	0.03
66	Winston-Salem, NC	0.03
67	Chattanooga, TN-GA	0.03
68	Minneapolis-St. Paul-Bloomington, MN-WI	0.03
69	Chicago-Naperville-Elgin, IL-IN-WI	0.03
70	Portland-Vancouver-Hillsboro, OR-WA	0.03
71	Denver-Aurora-Lakewood, CO	0.03
72	Fond du Lac, WI	0.03
73	Toledo, OH	0.03
74	Omaha-Council Bluffs, NE-IA	0.02

75	Augusta-Richmond County, GA-SC	0.02
76	Vineland-Bridgeton, NJ	0.02
77	Baltimore-Columbia-Towson, MD	0.02
78	Memphis, TN-MS-AR	0.02
79	Gainesville, GA	0.02
80	Madison, WI	0.02
81	Burlington, NC	0.02
82	Chambersburg-Waynesboro, PA	0.02
83	Cleveland-Elyria, OH	0.02
84	Raleigh, NC	0.02
85	Bowling Green, KY	0.02
86	Provo-Orem, UT	0.02
87	Evansville, IN-KY	0.02
88	Clarksville, TN-KY	0.01
89	Terre Haute, IN	0.01
90	Yakima, WA	0.01
91	Jackson, MS	0.01
92	Kennewick-Richland, WA	0.01
93	Des Moines-West Des Moines, IA	0.01
94	Cincinnati, OH-KY-IN	0.01
95	Boston-Cambridge-Nashua, MA-NH	0.01
96	Dayton, OH	0.01
97	Harrisburg-Carlisle, PA	0.01
98	Phoenix-Mesa-Scottsdale, AZ	0.01
99	Lynchburg, VA	0.01
100	Florence, SC	0.01
101	Racine, WI	0.01
102	Bremerton-Silverdale, WA	0.00
103	Scranton--Wilkes-Barre--Hazleton, PA	0.00
104	Birmingham-Hoover, AL	0.00
105	Charleston, WV	0.00
106	Idaho Falls, ID	0.00
107	Stockton-Lodi, CA	0.00
108	Ames, IA	0.00
109	Tulsa, OK	0.00
110	Palm Bay-Melbourne-Titusville, FL	0.00
111	Janesville-Beloit, WI	0.00
112	Bridgeport-Stamford-Norwalk, CT	0.00
113	Dallas-Fort Worth-Arlington, TX	0.00
114	Davenport-Moline-Rock Island, IA-IL	0.00

115	Reno, NV	0.00
116	Baton Rouge, LA	0.00
117	Knoxville, TN	0.00
118	Tampa-St. Petersburg-Clearwater, FL	0.00
119	Portsmouth, NH-ME	0.00
120	Niles-Benton Harbor, MI	0.00
121	Jefferson City, MO	-0.01
122	Waterloo-Cedar Falls, IA	-0.01
123	Lancaster, PA	-0.01
124	Rocky Mount, NC	-0.01
125	Fargo, ND-MN	-0.01
126	Albany, OR	-0.01
127	Boise City, ID	-0.01
128	Lakeland-Winter Haven, FL	-0.01
129	Fayetteville-Springdale-Rogers, AR-MO	-0.01
130	San Diego-Carlsbad, CA	-0.01
131	Reading, PA	-0.01
132	Charleston-North Charleston, SC	-0.01
133	Iowa City, IA	-0.01
134	Kalamazoo-Portage, MI	-0.01
135	Oxnard-Thousand Oaks-Ventura, CA	-0.01
136	St. Cloud, MN	-0.01
137	Pittsburgh, PA	-0.01
138	Champaign-Urbana, IL	-0.01
139	Sioux City, IA-NE-SD	-0.01
140	Joplin, MO	-0.02
141	Anniston-Oxford-Jacksonville, AL	-0.02
142	Owensboro, KY	-0.02
143	St. Louis, MO-IL	-0.02
144	Rochester, NY	-0.02
145	Oklahoma City, OK	-0.02
146	Midland, TX	-0.02
147	Mansfield, OH	-0.02
148	Lake Charles, LA	-0.02
149	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.02
150	Greeley, CO	-0.02
151	Sumter, SC	-0.02
152	Lincoln, NE	-0.02
153	Hanford-Corcoran, CA	-0.02
154	Modesto, CA	-0.02
155	Richmond, VA	-0.02

156	Jacksonville, FL	-0.03
157	Little Rock-North Little Rock-Conway, AR	-0.03
158	Houston-The Woodlands-Sugar Land, TX	-0.03
159	Hagerstown-Martinsburg, MD-WV	-0.03
160	Odessa, TX	-0.03
161	Allentown-Bethlehem-Easton, PA-NJ	-0.03
162	Sioux Falls, SD	-0.03
163	Springfield, IL	-0.03
164	Kingsport-Bristol-Bristol, TN-VA	-0.03
165	Columbus, GA-AL	-0.03
166	Olympia-Tumwater, WA	-0.03
167	Peoria, IL	-0.03
168	Austin-Round Rock, TX	-0.03
169	Mobile, AL	-0.03
170	Enid, OK	-0.03
171	Worcester, MA-CT	-0.03
172	Waco, TX	-0.03
173	Saginaw, MI	-0.03
174	Virginia Beach-Norfolk-Newport News, VA-NC	-0.03
175	Los Angeles-Long Beach-Anaheim, CA	-0.03
176	Decatur, IL	-0.03
177	Akron, OH	-0.04
178	Albany-Schenectady-Troy, NY	-0.04
179	Colorado Springs, CO	-0.04
180	Pine Bluff, AR	-0.04
181	South Bend-Mishawaka, IN-MI	-0.04
182	Charlottesville, VA	-0.04
183	Topeka, KS	-0.04
184	New Haven, CT	-0.04
185	Roanoke, VA	-0.04
186	Beaumont-Port Arthur, TX	-0.04
187	Flint, MI	-0.04
188	Winchester, VA-WV	-0.05
189	Sacramento--Roseville--Arden-Arcade, CA	-0.05
190	New York-Newark-Jersey City, NY-NJ-PA	-0.05
191	Huntington-Ashland, WV-KY-OH	-0.05
192	Manchester, NH	-0.05
193	Michigan City-La Porte, IN	-0.05
194	Muskegon, MI	-0.05
195	Santa Maria-Santa Barbara, CA	-0.05

196	Lebanon, PA	-0.05
197	Miami-Fort Lauderdale-West Palm Beach, FL	-0.05
198	Sierra Vista-Douglas, AZ	-0.05
199	Bismarck, ND	-0.05
200	Tucson, AZ	-0.05
201	Fort Smith, AR-OK	-0.05
202	Eau Claire, WI	-0.05
203	Spokane-Spokane Valley, WA	-0.05
204	Providence-Warwick, RI-MA	-0.05
205	New Orleans-Metairie, LA	-0.05
206	Lima, OH	-0.05
207	New Bern, NC	-0.06
208	Fort Collins, CO	-0.06
209	Waterbury, CT	-0.06
210	Springfield, OH	-0.06
211	Portland-South Portland, ME	-0.06
212	Lafayette, LA	-0.06
213	Salem, OR	-0.06
214	New Bedford, MA	-0.06
215	Syracuse, NY	-0.06
216	Logan, UT-ID	-0.06
217	Monroe, MI	-0.06
218	Muncie, IN	-0.07
219	Williamsport, PA	-0.07
220	Danbury, CT	-0.07
221	Bloomsburg-Berwick, PA	-0.07
222	Jackson, MI	-0.07
223	Weirton-Steubenville, WV-OH	-0.07
224	Riverside-San Bernardino-Ontario, CA	-0.07
225	Carbondale-Marion, IL	-0.07
226	Johnson City, TN	-0.07
227	Longview, WA	-0.07
228	Buffalo-Cheektowaga-Niagara Falls, NY	-0.07
229	Savannah, GA	-0.07
230	Elmira, NY	-0.07
231	Staunton-Waynesboro, VA	-0.07
232	Bellingham, WA	-0.07
233	Binghamton, NY	-0.07
234	Anchorage, AK	-0.07
235	Billings, MT	-0.07
236	Kokomo, IN	-0.07

237	La Crosse-Onalaska, WI-MN	-0.07
238	Youngstown-Warren-Boardman, OH-PA	-0.07
239	Midland, MI	-0.08
240	Morgantown, WV	-0.08
241	Altoona, PA	-0.08
242	Asheville, NC	-0.08
243	St. Joseph, MO-KS	-0.08
244	Erie, PA	-0.08
245	Bloomington, IN	-0.08
246	Gainesville, FL	-0.08
247	Columbia, MO	-0.08
248	San Antonio-New Braunfels, TX	-0.08
249	Jonesboro, AR	-0.08
250	Urban Honolulu, HI	-0.08
251	Kankakee, IL	-0.08
252	Canton-Massillon, OH	-0.08
253	Albany, GA	-0.08
254	Eugene, OR	-0.09
255	Lewiston-Auburn, ME	-0.09
256	Bloomington, IL	-0.09
257	Orlando-Kissimmee-Sanford, FL	-0.09
258	Albuquerque, NM	-0.09
259	Port St. Lucie, FL	-0.09
260	Gulfport-Biloxi-Pascagoula, MS	-0.09
261	Grand Island, NE	-0.09
262	Vallejo-Fairfield, CA	-0.09
263	Santa Rosa, CA	-0.09
264	Norwich-New London-Westerly, CT-RI	-0.09
265	Athens-Clarke County, GA	-0.09
266	Hattiesburg, MS	-0.09
267	Springfield, MO	-0.10
268	Tallahassee, FL	-0.10
269	Springfield, MA-CT	-0.10
270	Longview, TX	-0.10
271	State College, PA	-0.10
272	Florence-Muscle Shoals, AL	-0.10
273	Cumberland, MD-WV	-0.10
274	Danville, IL	-0.10
275	North Port-Sarasota-Bradenton, FL	-0.10
276	Utica-Rome, NY	-0.10

277	Napa, CA	-0.10
278	Yuba City, CA	-0.10
279	Ocala, FL	-0.10
280	Gettysburg, PA	-0.10
281	Dover, DE	-0.10
282	Auburn-Opelika, AL	-0.10
283	Las Cruces, NM	-0.10
284	Mount Vernon-Anacortes, WA	-0.10
285	Macon, GA	-0.10
286	Manhattan, KS	-0.10
287	Cheyenne, WY	-0.11
288	Wheeling, WV-OH	-0.11
289	Casper, WY	-0.11
290	Glens Falls, NY	-0.11
291	Dover-Durham, NH-ME	-0.11
292	Coeur d'Alene, ID	-0.11
293	Leominster-Gardner, MA	-0.11
294	Shreveport-Bossier City, LA	-0.11
295	Wilmington, NC	-0.11
296	Rochester, MN	-0.11
297	Fairbanks, AK	-0.12
298	Amarillo, TX	-0.12
299	Fayetteville, NC	-0.12
300	Dothan, AL	-0.12
301	Medford, OR	-0.12
302	Rome, GA	-0.12
303	Panama City, FL	-0.12
304	Duluth, MN-WI	-0.13
305	Texarkana, TX-AR	-0.13
306	Greenville, NC	-0.13
307	Corpus Christi, TX	-0.13
308	Corvallis, OR	-0.13
309	Bend-Redmond, OR	-0.13
310	Grand Forks, ND-MN	-0.13
311	Pittsfield, MA	-0.13
312	Carson City, NV	-0.14
313	Farmington, NM	-0.14
314	Lubbock, TX	-0.14
315	Alexandria, LA	-0.14
316	Grand Junction, CO	-0.14

317	Valdosta, GA	-0.14
318	Pensacola-Ferry Pass-Brent, FL	-0.14
319	Cleveland, TN	-0.14
320	Wenatchee, WA	-0.14
321	Mankato-North Mankato, MN	-0.14
322	El Paso, TX	-0.14
323	Rapid City, SD	-0.15
324	Sherman-Denison, TX	-0.15
325	Goldsboro, NC	-0.15
326	Cape Coral-Fort Myers, FL	-0.15
327	Lawton, OK	-0.15
328	Harrisonburg, VA	-0.15
329	Wichita Falls, TX	-0.15
330	Las Vegas-Henderson-Paradise, NV	-0.16
331	Great Falls, MT	-0.16
332	Beckley, WV	-0.16
333	Missoula, MT	-0.16
334	Monroe, LA	-0.16
335	Sebastian-Vero Beach, FL	-0.16
336	Prescott, AZ	-0.16
337	San Luis Obispo-Paso Robles-Arroyo Grande, CA	-0.16
338	Santa Cruz-Watsonville, CA	-0.16
339	Killeen-Temple, TX	-0.16
340	Lawrence, KS	-0.16
341	Pocatello, ID	-0.17
342	Bangor, ME	-0.17
343	Crestview-Fort Walton Beach-Destin, FL	-0.17
344	Laredo, TX	-0.17
345	Bay City, MI	-0.17
346	St. George, UT	-0.17
347	Deltona-Daytona Beach-Ormond Beach, FL	-0.17
348	Naples-Immokalee-Marco Island, FL	-0.18
349	College Station-Bryan, TX	-0.18
350	Walla Walla, WA	-0.18
351	Barnstable Town, MA	-0.18
352	Salisbury, MD-DE	-0.18
353	Cape Girardeau, MO-IL	-0.18
354	Victoria, TX	-0.18
355	Parkersburg-Vienna, WV	-0.18
356	Lake Havasu City-Kingman, AZ	-0.18

357	Redding, CA	-0.18
358	Abilene, TX	-0.18
359	Ithaca, NY	-0.19
360	San Angelo, TX	-0.19
361	Kingston, NY	-0.19
362	Tyler, TX	-0.19
363	Pueblo, CO	-0.19
364	Atlantic City-Hammonton, NJ	-0.19
365	Watertown-Fort Drum, NY	-0.20
366	Brunswick, GA	-0.20
367	Santa Fe, NM	-0.20
368	Chico, CA	-0.21
369	Hammond, LA	-0.21
370	Flagstaff, AZ	-0.21
371	Daphne-Fairhope-Foley, AL	-0.21
372	Hot Springs, AR	-0.22
373	Hinesville, GA	-0.22
374	Gadsden, AL	-0.22
375	Johnstown, PA	-0.22
376	Homosassa Springs, FL	-0.23
377	East Stroudsburg, PA	-0.23
378	Grants Pass, OR	-0.23
379	Jacksonville, NC	-0.24
380	McAllen-Edinburg-Mission, TX	-0.24
381	The Villages, FL	-0.24
382	Punta Gorda, FL	-0.25
383	Sebring, FL	-0.25
384	Brownsville-Harlingen, TX	-0.26
385	Hilton Head Island-Bluffton-Beaufort, SC	-0.26
386	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	-0.27
387	Kahului-Wailuku-Lahaina, HI	-0.29
388	Ocean City, NJ	-0.32

Source: Brookings analysis of Webb (2019)

Acknowledgements

The Metropolitan Policy Program at Brookings would like to thank the following for their generous support of this analysis and our metropolitan advanced economy work more broadly: the Arconic Foundation, Bank of America, Central Indiana Corporate Partnership and BioCrossroads, Microsoft, the Ralph C. Wilson Jr. Foundation, Mario Morino, and Antoine van Agtmael. The program is also grateful to the Metropolitan Council, a network of business, civic, and philanthropic leaders that provides both financial and intellectual partners of the Program.

The authors are indebted to many colleagues who offered significant input with regard to the substantive development of the analysis.

Special thanks go to Michael Webb who shared his data and vision and provided invaluable insights through multiple conversations about his work.

The authors would like to thank the following colleagues outside of Brookings for important insights or help: James Bessen, Joanne Harrell, David Johnson, Frank Levy.

Within Brookings, the following staff offered significant substantive input: Alan Berube, Lavea Brachman, Annelies Goger, Chris Howie, Julia Kraeger, Amy Liu, Joseph Parilla, Martha Ross, Adie Tomer, and Darrell M. West. In addition, the authors wish to thank Anthony Fiano, Michael Gaynor, and David Lanham for their editorial and communications expertise. Thanks to Luisa Zottis for layout and graphic design.

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