Automation and Artificial Intelligence:

Backward and Forward,

Place by Place

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Computers, Artificial Intelligence, and the American Worker: Recent and Future Impacts of Automation

Work in Progress: Measuring and Adapting to the Labor Market Impacts of Automation

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1. Introduction

First technologists issued scary dystopian alarms about the power of automation, including artificial intelligence (AI), to destroy millions of jobs.

Then came a correction of sorts, with a wave of reassurances this year that in aggregate technology will displace many workers but not end work.

Now the current discourse holds that the robots are coming but it won’t be an apocalypse. Automation, rather, is more a general problem for tomorrow or next year than a crisis for today.

Yet, while the spread of automation may not entail a robot apocalypse for everyone, newer findings have steadily suggested a number of more disturbing and immediate sub-aspects of increasing automation.

Not only will some industries be much more affected by technology than others, but several studies have suggested that some places are much more vulnerable to job displacement than others. Still other analyses have suggested that different demographic groups might face greater disruption, ranging from men to minorities. All of which underscores the mixed and incomplete knowledge about how automation and similar technologies will impact the workforce.

To fill in some of the blanks and provide a multi-dimensional picture of automation’s big picture and more segmented potential impacts, the pages that follow provide both backward- and forward-looking analyses of how the advent of digital technologies is reorienting labor markets as well as a policy agenda for national and state and local response.

The analysis begins by defining and conceptualizing automation so that leaders and citizens can better understand how it tends to influence labor markets. After that, the report employs established occupation-based statistical approaches to quantify and map the disparate observed and projected impacts of automation on job growth and change over the years 1980 to 2016 and 2016 to 2030. Special attention is applied to digging beneath the national top-line statistics to explore industry, geographical, and demographic variations. Finally, the report suggests a number of implications for national and stateand local policymakers.

In keeping with these discussions, the present report can be interpreted as cause for both reassurance and disquiet, with the near future resembling the near past.

Yet, a future that resembles the recent past is hardly cause for cheer. As the retrospective analysis here suggests, the first era of digital automation was one of traumatic change in the labor market, defined especially by the “hollowing out” of the labor market, with employment and wage gains coming only at the high and low ends of the skill distribution. Such dynamics have led to social, economic, and political turmoil in the United States. That our analysis projects more of the same in the next decade-plus (with the possibility of faster, broader disruption) will not, therefore, be comforting. It argues instead for urgency and for taking more and greater precautions, ranging from stepped-up provisions for lifelong learning, improved labor-market transitions, and more helpful programs to address the individual and regional hardships of the vulnerable.

In that sense, the following assessment may not warrant dread, but it surely requires attention and action.

2. Automation: What it is, how to conceptualize it, how it impacts workers

So, what do we mean by automation? How should we conceptualize it as an economic issue—nationally but also for local labor markets? And, how should one think about the interaction between automation and employment globally but also locally?

Defining automation

Automation is not new. From the beginning, humans have constantly developed new and superior tools and technologies to produce greater economic output with less human effort. Some of these advances have been transformational, with broad impact across many sectors of the economy—such as the steam engine, electricity, and information technologies. Others gains have been more specialized—for example, mechanized weaving looms, industrial robots, or automated teller machines.

Regardless of its scope, automation fundamentally exists to substitute work activities undertaken by human labor with work done by machines, with the aim of increasing quality and quantity of output at a reduced unit cost. This ability to increase workers’ productive capacity has historically enabled humans to transition out of physically difficult, mundane, or menial labor, and in so doing, raised the standard of living.

And yet, while the benefits of automation to the economy as a whole are clear, the impact on workers is less certain.

Historically, workplace substitution by machines has freed-up humans to focus on higher-value tasks or to create new ones. The Agricultural and Industrial revolutions of the 18th and 19th centuries, for example, were periods of immense workplace automation—and yet, the share of the population engaged in work actually rose as new demand engendered new products, services, and work.

But automation hasn’t always carried positive news for workers. While there have historically been enough jobs to go around, the impact on wages has been more ambiguous. Similarly, workplace disruption can carry substantial costs for those directly affected, since such workers may need to upgrade their skills or move into new roles. No wonder that the current surge of artificial intelligence (AI), robotics, and other digital technologies has raised fresh concerns about the future availability and nature of work.

Conceptualizing automation

So, how should we conceptualize automation as an economic matter for analysis? To understand the impact of automation on employment, after all, one must first be able to quantify it as an economic activity. Yet this remained a practical and conceptual challenge for many years.[[1]](#endnote-1) However, in the early 2000s, economists David Autor, Frank Levy, and Richard Murnane advanced a paradigm-shifting framework for analyzing the impacts of automation on employment and wages.[[2]](#endnote-2) With this work, Autor, Levy, and Murnane showed that statistical analysis could better measure the impacts of automation on workplace activities if it considered what people *do* at work (tasks), rather than the *capabilities* they possess to carry-out those activities (skills).

In this fashion, the so-called task model now presides as the starting point for understanding automation’s implications for the labor market. First off, the task framework makes clear that a job is a bundle of tasks, to which workers apply skill endowments in exchange for wages.[[3]](#endnote-3) Some of these tasks may become automated. Others may not. Skills belong to workers, which can be ported to other jobs—even those with a different task composition.

Second, task-based models allow researchers to more precisely pinpoint skill requirements. Because of data limitations, economists often fail to distinguish skills from educational attainment or relative wages. In reality, skill requirements vary widely *within* educational attainment and wage groups. For instance, a cashier at a fast food restaurant and a groundskeeper may both have high school educations and receive similar wages, but are far from comparable in the types of skills necessary to perform their respective jobs. Task models specify which activities occur in a job and therefore the skills required to carry them out. This allows for a more granular understanding of how automation affects them.

Finally, task-based models provide a prism for viewing the comparative advantage of man and machine, which compete based on the overall cost and effectiveness of completing tasks. In production, there are both “labor tasks” (things humans do) and “capital tasks” (things machines do). Critically, the boundary between the two is both permeable and evolutionary. Humans are more flexible and adaptive, and therefore better suited for workplace activities that are new or complex. Machines are better suited for tasks that are repetitive or well understood, and therefore more easily codified.[[4]](#endnote-4)

How automation impacts workers

The concept of automation, and the use of task-based models to analyze it, leads to some general rules that seem to govern the interaction of machines and workers. With those in mind, it is possible to conceptualize the net impact of automation on employment and wages.

**General tendencies**

To start with, here are six basic tendencies in the workings of automation and its interplay with human labor that may help in assessment:

* **Automation substitutes for labor**. This is the fundamental purpose of workplace technology. If a machine can do a task currently done by humans, it will do it with greater precision, speed, and at a lower cost. But, there are limitations to substitution, both because of technological constraints (machines will never do it all) and factor price adjustments (if automation causes wage declines, labor becomes more competitive).[[5]](#endnote-5)
* **Machines substitute for tasks, not jobs**. A job is a collection of tasks. Some of those tasks are best done by humans, others by machines. Even under the most aggressive scenarios of technological advance, it is unlikely that machines will be able to substitute for *all tasks* in any one occupation.[[6]](#endnote-6) This implies constant change but also a persistent need for human labor, even in highly automated contexts.
* **Automation also complements labor**. Generally, whatever workplace activity isn’t taken over by automation is complemented by it—making each remaining human task more valuable. This makes labor more valuable, and the increased productivity generally (though not always) translates into higher wages.
* **Automation frequently increases demand, creating jobs**. Machine substitution for labor improves productivity and quality and reduces the cost of goods and services. This may—though not always, and not forever—have the impact of increasing employment in these same sectors. This is because the automation-driven cost and quality improvements can increase demand for these goods and services to a degree that offsets any would-be job losses from automation. Similarly, the productivity and wage gains brought by automation can result in workers having more disposable income, which increases consumption and hence employment in other industries.[[7]](#endnote-7)
* **Capital and labor augmentation spurs innovation**. When machines handle routine, time-consuming activities, human capacity is freed-up to create new products and new tasks. Think of the explosion of new consumer banking services that supported local branch office expansion, even as ATMs reduced the need for tellers to conduct simple transactions—expanding employment of bank tellers in the process, and changing the skill requirements for those roles.[[8]](#endnote-8) Note, too, that in the information era, half of employment growth in the U.S. economy between 1980 and 2007 was accounted for by occupations with new job titles (i.e. new roles).[[9]](#endnote-9)
* **Technological possibility is not the same as technological reality**. In this regard, it is a mistake to equate technological potential with likely projected outcomes. McKinsey & Company estimates that the U.S. achieves just 18 percent of its “digital potential.” More broadly, there are many reasons why technological adoption falls short of potential, including: technical feasibility, deployment challenges, labor competition, regulatory and social barriers, and institutional factors, among others.[[10]](#endnote-10)

**What determines the number, composition, and wages of jobs**

In terms of what determines the net impact of automation on employment and wages, Autor provides a simplified framework.[[11]](#endnote-11) In it, he highlights three primary dynamics:

* **What technology doesn’t replace, it complements**. Generally speaking, machines complement whatever workplace activities they do not substitute for. Workers who supply tasks that automation complements (i.e. tasks that aren’t substituted for by machines), are more likely to benefit from automation than are workers who supply tasks that machines can complete.
* **Wages will be determined by the ease with which roles in demand can be filled**. Since the remaining tasks completed by humans are complemented by machines, one would first expect wages to increase as these workers become more productive. But, wage gains can be mitigated, in full or in part, by the ease with which these roles can be filled by other workers—or what economists call the “elasticity of supply of labor” (the responsiveness of labor supply to an increase in demand for a given role). For example, if technology similarly increases the productivity of both physicians and street food vendors, holding all else equal, we would expect wage gains to be larger for physicians because the barriers to entry (many years of education, training, and certification) for physicians are much higher. Conversely, it would be fairly easy for many new workers to flood the market for street food venders, which might well dampen productivity-driven wage increases.
* **The size of industries—and the number of jobs in them—will be determined by the complex interaction of consumers’ responses to automation-driven price and quality improvements and how consumption responds to automation-driven wealth changes.** In this respect, machines and AI very plainly do substitute for labor. But two offsetting dynamics basic to economies in general may also mitigate some of that displacement. In the first effect, machine-driven quality or cost improvements (as noted above) can actually *increase* employment in particular industries. This happens as the product improvements increase demand and therefore increase demand for the workers, who, aided by machines, produce the goods or services. In such cases, automation increases the net number of workers in the automated industry—sometimes substantially so. This is what Acemoglu and Restrepo call the “productivity effect.”[[12]](#endnote-12) As an example, James Bessen of Boston University describes huge declines in the price of cloth in the 1800s due to mechanized looms led to a net increase in textile jobs. With the price of clothing much cheaper, the ability of households to expand wardrobes exploded, therefore increasing the demand for weavers even in the face of substantial workplace automation.[[13]](#endnote-13)

The second countervailing dynamict might be called the “wealth effect.” This dynamic reflects how the demand for goods or services (and the labor to produce them) changes as society becomes wealthier thanks to automation-driven productivity increases. Through this effect, the increased wealth generated by machine-driven productivity gains can support increased consumer demand across the board and even the creation of entirely new labor-intensive tasks. This dynamic can also reinstate human labor. Think of the present rising demand for fulfillment center workers and yoga instructors. Fast automated fulfillment has begotten more of that while societal wealth creation has spurred new demand for yoga classes. In short, the size of industries and the demand for workers in them is determined not just by the displacement effect of machines, but how that interacts with the productivity and wealth effects of automation. The interaction of these factors is complex, and may fully or partially offset the displacement of workers.[[14]](#endnote-14)

In sum, recent scholarship provides an incisive framework for thinking about the impacts of automation and AI on local communities that is both clarifying and open-ended.

On the one hand, the task framework identifies a set of basic dynamics that affect how automation and AI affect labor markets. On the other hand, the interaction of these dynamics is complex, to the point that productivity, wealth, or other effects may fully or partially offset the displacement of workers, and with variations across place.[[15]](#endnote-15) As a result, the total effect of these crosscutting patterns can be hard to predict.[[16]](#endnote-16)

Which is why it is important to both assess past automation trends with data from recent experience as well as explore possible future trends using best-guess projections.

With the effects in question of critical interest to workers, industries, and regions alike, it is important to continuously test the conceptual insights of the task framework against experience, and also to project them forward to anticipate potential trends and impacts across the economy.

What is needed, then, is more inquiry into automation’s current dynamics and likely evolution—occupation by occupation, industry by industry, and region by region.

# 3. Methodology

To explore the impact of automation on the workforce nationally and across regions, this report utilizes data from public and private sources to support two complementary analyses. The first analysis looks backward at the impact that digital automation has had on employment during what we call the “IT era”—a period characterized by the rise of information technology and especially the personal computer. The second analysis looks ahead, to reasonably speculate about how the next wave of digitally powered automation may impact employment in what we are calling the “AI era”—a period that may well be dominated by the adoption of artificial intelligence.

## Backward-looking analysis

To document the ways in which automation has impacted the labor market in the last few decades, we utilize and extend the data and methodology used by economists David Autor and David Dorn in their work on shifting employment patterns due to technological change.[[17]](#endnote-17) These authors have generously provided their analytical files for the period 1970 through 2012. To incorporate more current information, we have extended these files through 2016. The approach involves several steps.

To establish the degree of IT-era automation across the economy, the analysis first adopts Autor and Dorn’s use and organization of data from the U.S. Department of Labor’s “Dictionary of Occupational Titles,” a publication that documents occupational workplace activities and requirements going back in time.[[18]](#endnote-18) Following Autor and Dorn, we have grouped each occupation in the workforce into one of three categories based on the predominant task content of that role: abstract, manual, or routine.

Routine occupations are generally most susceptible to automation because they involve a high degree of tasks that are repetitive and are therefore easily codified. Critically, routine occupations transcend traditional educational requirement categories. They can be found in areas that require some post-high school education (e.g. sales, clerical-retail, and administrative roles) or in occupations that require nothing more than a high school diploma (e.g. production and extraction roles).

Abstract and manual occupations involve tasks that are either complex and therefore difficult to codify, or take place in physical environments that are difficult to control. In both such cases, automation is more of a challenge. Abstract roles—typically in management, technology, or finance—tend to require more formal education and skills such as creativity, persuasion, intuition, and problem solving. Manual jobs, on the other hand, tend to require less education and require physical adaptability, dexterity, visual and auditory perception, and interpersonal engagement. Examples include construction, transportation, or service occupations.

With the above classification in place, the analysis uses the decennial Census microdata for 1980, 1990, 2000, and 2010 and the American Community Survey (ACS) microdata for 2005, 2012, and 2016 to examine changes in the U.S. labor force by detailed occupations and geographies.

Because occupational codes and geographic boundaries change over time, the authors constructed time-consistent occupational codes and geographic areas. This required some tradeoffs in terms of the granularity of occupations, but still yielded a set of 330 time-consistent occupations spanning the entire U.S. labor market and 722 Commuting Zones (CZs), which cover all metropolitan and rural areas across the entire mainland of the United States.

With these figures in hand, we are able to observe employment and wage changes over several decades at the national and local level, and determine how these changes vary across the three major task-content job types: routine, abstract, and manual (though we will focus on routine and non-routine, by combining the latter two). This analysis provides insight into how automation has impacted employment during the IT-era so far.

## Forward-looking analysis

Our forward-looking analysis looks at the onset of the AI era and is rooted in the “automation potential” of current workplace roles—specifically the extent to which the current task content of a particular occupation could be technically substituted for in the future given currently demonstrable technologies. Employing such ratings of “automatability” we then assess the automation exposure, or lack thereof, of U.S. industries; geographies (the nation as a whole, states, metropolitan areas, and counties); and demographic groups.

Estimates of each occupation’s automation potential come from the McKinsey Global Institute, which provided us with figures from their 2017 report “A Future that Works: Automation, Employment, and Productivity.”[[19]](#endnote-19)Employing an exhaustive research procedure, McKinsey calculated values for the “technical potential for automation” for each of the more than 800 occupations spanning the entire U.S. labor force (under current occupational classifications). Each value falls between 0 percent and 100 percent, and refers to the share of current task content that could be automated by 2030 or in next decades based on currently demonstrated technologies. (For more detail on how McKinsey tabulated these figures see their report’s Technical Appendix).

To measure the extent automation may affect the workforce and regional economies, we apply McKinsey’s task automation values to data on occupational employment at the level of the U.S., states, metropolitan areas, and counties, provided to us by Economic Modeling Systems (EMSI)—a data vendor specializing in labor markets.[[20]](#endnote-20) EMSI provided the data to us at both the six-digit SOC occupation (784) and three-digit NAICS industry (87) classification levels, both historically and forecasted 10 years forward. (Note: Some occupations in the McKinsey data were consolidated into broader occupation groups in the EMSI segmentation).[[21]](#endnote-21)

With these data in hand, the automation potential of each occupation from McKinsey was combined with the EMSI occupational-industry employment mixes for geographies, and with economic data (output and employment) for the entire economy so as to make estimates about what occupations, industries, and places are likely to add or lose employment. The economic data on output and employment employed here are produced by Moody’s Analytics, and are available both historically (to assess prior performance of industries or geographies) and forecast into the future.

## Strengths and limitations

The analysis that follows has strengths and weaknesses, and as such, the figures and trends here should all be viewed as prompts to discussion.

The main strength of the analysis is that it employs several credible datasets to provide both historical and forward-looking estimates of the job, industry, and regional impacts of automation, based on fine-grained occupational ratings. The result speaks both to big-picture trends and local questions about how those trends are manifested in particular jobs and industries in particular places.

In doing so the present work draws on strong previous work and several recognized methodologies, including solid previous efforts to estimate the localized impacts of automation.[[22]](#endnote-22) These efforts run from analyses by Autor and others, Benedikt Frey and Michael Osborne, Daron Acemoglu, and Morgan Frank to the McKinsey Global Institute, Governing magazine, the New America think tank, and the National League of Cities.[[23]](#endnote-23) By utilizing alternative data sources and methodologies, this report seeks to expand upon the work of others and provide additional nuance to ongoing debates about the extent of economic disruption future rounds of technological change portend.

With that said, our approach does carry with it certain limitations as well, that, for the most part, affect the forward-looking analysis.

To begin with, the future automation potential figures, while robust, only deal with the current task content of current jobs and current capabilities of technology. This outcome is unavoidable, as we don’t know what tomorrow’s task content will be—we can only rely on what we know about today, and where we think technology will go. New tasks and occupations will emerge, as will new technologies and new industries, and existing roles will adapt to evolving task demands as human ingenuity and technology alike advance.[[24]](#endnote-24) Our work is significantly limited in this regard. For example, recall from before that during the 1980s, 1990s, and 2000s half of employment growth came from occupations that didn’t exist before. [[25]](#endnote-25) Similarly, we are unable to say what any particular automation potential figure spells for future employment or wages because of the complex set of factors described before.

Secondly, as described earlier, there is a well-established history of divergence between technological possibilities and technological adoption. We have no ability to assess how the gap between “automation potential” (which our figures are based on) and “actual adoption” (what will actually occur) will evolve, so our estimates should be seen as an upper bound—perhaps even an extreme one. Our figures describe what is possible—not what is likely. In that regard, one might interpret our figures more as a degree measure of workplace task *change* rather than as a predictor of employment or wages per se.

Third, while we don’t specifically address the timeline of automation’s absorption, it is important: The faster automation takes place, the more disrupting it will be in the workplace and the more difficult it will be for workers to adapt. And yet, predicting these timelines is a challenge. Instead, we’ll direct readers to the McKinsey work. Their adoption estimates are both responsibly variable and distant in the future. They predict that technical automation *potential* makes major strides by 2030, with full potential being achieved as early as 2040 or as late as 2050. For *adoption*—that is, automation potential after adjusting for technical, economic, and social factors affecting the pace of uptake—things begin to pick-up by 2045 with full adoption no earlier than 2065. Even under their most aggressive scenarios, then, it will take at least a few decades for the economy to feel the impact of currently emerging technologies. Said differently, we might be thinking about preparedness for changing workplace requirements in terms of generations (not in terms of years)—something that is encouraging from a policy standpoint, particularly because young workers can be trained from the beginning for roles that show the least susceptibility to future automation and steered away from those with the most.

Fourth, and related to the above, much of the impression created by our analyses and others depends on the cut-off used to characterize “high” susceptibility to automation. Along these lines, we deem a 70-percent share of automatable task content in an occupation by 2030 or 2040 as “high” risk. However, while this threshold is consistent with many other studies and aligns with statistical breaks in the occupational data, it bears noting that this is not a theoretically grounded threshold. Rather, it is a mostly arbitrary one. In fact, we performed a number of statistical tests that indicate a more realistic threshold for “high” could be between 75 percent and 85 percent. However, for now, we’ll stick with widely-employed thresholds. More broadly, it bears noting that assessing qualitative and quantitative differences in the extent and pace of task-level job change in occupations remains an underdeveloped aspect of the preexisting literature on automation.[[26]](#endnote-26)

Fifth, while a significant portion of our analysis focuses on how the impact of automation will vary across geographies, a key input into our analysis—the McKinsey automation potential estimates for each occupation—are produced at the national level. As a result, our estimates for how automation might affect regions differently depend purely on the current industrial and occupational mix of these states, metropolitan areas, and counties. Surely, some regions will uptake automating technologies more aggressively—or more effectively—than will others. However, we have no good information to say what this will look like, at least not at a level that we feel is sufficiently defensible. Given that, consumers of data should bear in mind that our automation potential figures do not account for local adoption differences.

Finally, and related to all of the above points, the economy is a dynamic system that will evolve, expand into new areas, and reallocate among existing activities. These factors make it impossible to predict how the economy will reshape itself over the coming decades. As a result, the present analysis should be seen more as a measure of which occupational areas and geographies are the most likely to see great change—rather than predictive of the number of jobs available in a particular area or the size of sectors that employ those roles.

4. Findings

## To gauge the nature of automation dynamics in the U.S. labor market and across places, multiple datasets as described above are utilized here to assess both past trends and to provide a picture about some possible future ones.

## This assessment first reviews the impacts of automation in the recent IT-era. Then it forecasts the potential future progress of automation in the AI-era up to 2030.

## Automation in the IT era

To the extent the spread of IT through the economy since the 1980s represents a first episode of digitally driven automation, it provides a source of initial insights about current and future change.

National and regional patterns of growth and displacement from the past several decades therefore provide hints about possible future patterns of change.

**1. Overall employment has grown in the IT era nationally, but the middle of the wage continuum has been “hollowed out”—with changes in employment and wages greatest at the high and low ends of the wage distribution.**

One thing that has not happened during the past several decades of digitally powered automation associated with the widespread adoption of the personal computer in the United States is any wholesale decline in employment. Over the years 1980 to 2016, the economy created 54 million net new jobs, even as exponential gains in computer adoption and processing speed were realized.[[27]](#endnote-27) During that time, the ratio of jobs to the civilian non-institutionalized population over age 16 actually increased from 55 percent in January, 1980 to 57 percent in December, 2016. That implies that automation does not necessarily diminish the overall pool of available jobs, even in periods of rapid technological advance.

And yet, automation does seem to have coincided with a significant hollowing out of the employment distribution in the last nearly four decades. In this regard, work led by David Autor and his collaborators documents a striking polarization of the U.S. labor market, whereby the demand for work at both the high and low ends of the wage distribution has grown, even as it has slumped in the middle—contributing to a reduction of middle-skill employment.[[28]](#endnote-28) Nor is the United States is alone in facing this dynamic—this same trend has also been documented across the whole of Western Europe.[[29]](#endnote-29)

Figure X, derived from Autor and Dorn, illustrates these trends in the United States. As such, the graph plots smoothed changes in employment (the dark blue line) and wages (the light blue line) between 1980 and 2016 ordered by occupational wage percentile at the start of the period. Lower paying jobs (that generally imply lower education requirements) lie to the left while higher paying, higher-education jobs range to the right. Overall, it is very clear that both employment growth and wage progress have slumped in the middle of the skill distribution for occupations such as production helpers and clerical workers during the first era of widespread digital automation. Gains have come predominently at the low and high ends of the scale and those have become more pronounced over time.



**2. The middle-wage jobs in decline are also most closely associated with routine task content—which made them susceptible to automation.**

Of course, the U-shaped employment and wage curves of the 1980 to 2016 period might only coincide with the rise of digital automation. Why does it increasingly appear that automation causedthem? Data and the task framework provide some insight. Figure X shows the same horizontal axis as above (distribution of wages in 1980 from low to high), but instead, the vertical axis shows the share of occupations in each percentile grouping that are predominantly comprised of rote, or routine, or codifiable, tasks (as opposed to being predominantly non-routine physical, interpersonal, or higher-level cognitive skills).



Before, employment and wage growth reflected a U-shaped relationship between wage levels in 1980 and subsequent *growth* patterns. Lower and higher skilled occupations saw gains but middle-waged work slumped. But here, a plotting of the routine task content of occupations reveals a strikingly symmetric inverted U. This means the same occupations that saw relative declines (slower or negative job growth; slower real wage growth) during last few decades were also much more likely to be oriented toward routine tasks. Typical examples include factory workers and office clerical staff. And as it happens these are the same types of tasks that have been most susceptible to automation (as well as offshoring—another confounding factor) in the IT era.[[30]](#endnote-30)

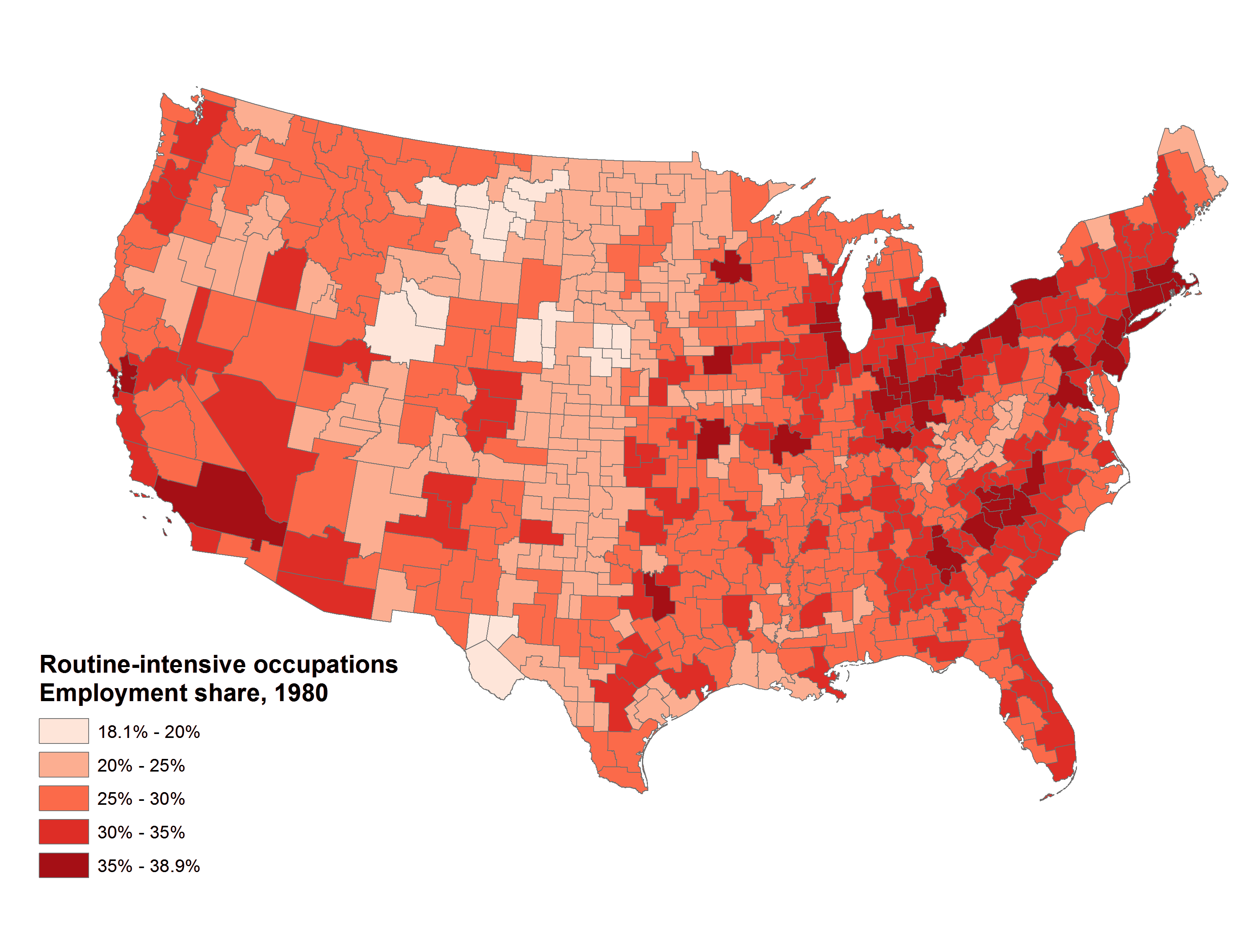
The takeaway: Automation has substituted for many jobs, but not all jobs—and it has complemented other work and so also supported growth. In this fashion, technological progress in the years from 1980 to the 2000s drove a pronounced polarization of U.S. employment and wages that has only shown signs of easing somewhat in the last few years.[[31]](#endnote-31) Central to how this has played out is the fact that machine substitution for human tasks requires an understanding of workplace activitites to the point where they can be codified (and therefore programmed). This feature of automation has ensured that jobs with repetitive task content—whether of a physical or cognitive nature—have been placed at a comparative disadvantage relative to machines. This is why production jobs in factories, as well as clerical, sale, and administrative jobs in offices, have been at the forefront of recent automation fears.

**3. Manufacturing and office administration-oriented regions areas of the Midwest, Northeast, South, and West Coast with the highest concentrations of routine employment were also the places that saw the largest shift to low-wage service employment in the information age.**

A look at the geographic distribution of routine jobs in 1980, meanwhile, begins to suggest how different communities have been exposed to significant displacement via automation.

To be sure, routine work was spread widely throughout the country at the onset of the heaviest phase of the IT era as Figure X shows—with virtually all regions except the Great Plains containing commuting zones with substantial rote or routine task content in occupations.

**Routine occupation share of employment by commuting zone, 1980**



*Source: Brookings analysis of Autor and Dorn (2013)*

Yet with that said, the incidence of routine-oriented work differed widely across places in 1980.

Without doubt some of the the highest concentrations of routine work were in the manufacturing belts of the Midwest, Northeast, and Southeast, ranging from Michigan to Massachusetts to North Carolina. Communiting zones (CZs) like **Detroit** (37.7 percent); **Greensboro, N.C.** (37.6 percent), and **Providence, R.I.** (37.0 perent) are indicative of this pattern. Moreover, there is also a strong positive correlation between the routine share of employment in a CZ in 1980 and the manufacturing share of employment in that same region—a relationship that sharpens at the high end of the routine employment distribution (in other words, the highest routine-intensive regions were also the highest manufacturing-intensive).[[32]](#endnote-32)

And yet, knowledge-intensive cities such as **New York**, **San Francisco**, and **Washington, D.C.** also ranked high for their 1980 routine-work intensity. Routine-work percentages in these knowledge hubs also reached into the high 30 percent range and underscore the early office-clerical focus of these cities in 1980 (combined with continued modest manufacturing in New York and San Francisco). By contrast, local labor markets specialized in such industries as hospitality and tourist services (like **Las Vegas**); education and health (like **Raleigh, N.C.**); or construction, mining, and energy (like **Houston**) tended to display relatively low routine employment. In short, the heavily rules-based nature of manufacturing and office-clerical work in the 1980s was a significant determinant of local task content then and going forward, with large implications for the disruption of work by automation in the IT era.

As to what happened next, it has been dramatic. After 1980, the rapid adoption of the personal computer and “digitalization” of the economy greatly reduced the cost of automating routine codifiable tasks.[[33]](#endnote-33) This, in turn, drove a decline in routine jobs nationally, which meant in turn that routine-work oriented regions (especially manufacturing and clerical regions) were hit especially hard by the widespread deployment of automation (along with the arrival of low-cost foreign imports with the onset of globalization). These regions therefore saw not only the “hollowing out” of their middle-skill job base, but also—as middle-skill jobs declined—a massive shift of middle-skilled, often non-college educated workers into lower-wage local service activities.

The scatterplot below shows how this has played out, as the CZs with the largest shares of routine jobs in 1980 also saw the largest increases, through 2016, in their share of workers without a college education employed in low-skill service occupations.



In considering this transition, meanwhile, it is important to recognize that the low-skill service occupations that proliferated in the IT era are not the relatively better-paying ones in “service” industries ranging from health care to communications to business. Rather, the occupations that spiked in the 1990s and 2000s are those that involve assisting or caring for others, such as, for example, food service workers, security guards, janitors, gardeners, , cleaners, home health aides, child care workers, hairdressers, and recreational occupations. And while these increases in service employment did entail continued employment opportunities, rather than joblessness, they provided work at lower wages than what many of these workers previously earned in middle-wage manufacturing or clerical jobs.

In this regard, the expansion of digitally powered automation in the decades after 1980 played a large role in ensuring that the regions most heavily concentrated in routine (often manufacturing or clerical) work experienced some of the largest shifts into low-wage services employment as robots and computers substituted for large numbers of middle-skill jobs and helped create new consumer demand for lower-end services.

Manufacturing centers like **Winston-Salem, N.C.**, **Chicago**, and **Pittsburgh** as well as transitioning knowledge centers like **New York**, **San Francisco**, and **Washington, D.C.**, all of which had upward of 32 percent of their jobs in routine-intensive employment in 1980, experienced increases in low-skill service employment of more than 12 percentage points between 1980 and 2016.

By contrast, **Las Vegas** (a longstanding international tourism hub), **Raleigh, N.C.** (home of North Carolina State University and a number of large hospitals), and **Modesto, Calif**.(in the heart of California’s agriculturally rich Central Valley) allhad lower levels of routine work in 1980 and saw much more muted increases in low-skill service work in the neighborhood of 4 percentage points.

In sum, the places with the largest exposure to routine work (and implicitly automation, especially in the production sector) saw some of the greatest increases of lower-skill service employment in the IT era as their relatively larger routine, or middle-skill, workforces came under pressure from automation. Conversely, other metro areas with lower shares of routine employment saw less dramatic labor market transitions. In that fashion, the local impact of automation during the IT era from 1980 to today varied significantly depending on the degree of routine or rote task content in the local job mix.

## Automation in the AI Era

Now that the IT era is transforming into an AI era pervaded by more powerful digital technologies. Which raises the question: What will the next phase of the interplay between automation and employment look like? Will it be different?

The findings on national, regional, and social-group trends utilize data on the current task content of occupations as well as McKinsey’s estimates of workplace susceptibility to automation in the next few decades to get a sense of which jobs, industries, places, and demographic groups may be most exposed to disruption in the coming decades.

Several points emerge at the national level:

**4. Automation will affect tasks in virtually all occupational groups in the future but will likely continue to have a muted net impact on total employment**

Intelligent machines may well take over from humans many traditionally protected task areas, but expert opinion converges around several broad areas that appear to be particularly challenging for machines now and likely will remain so in the future. This work that machines can’t readily do includes:

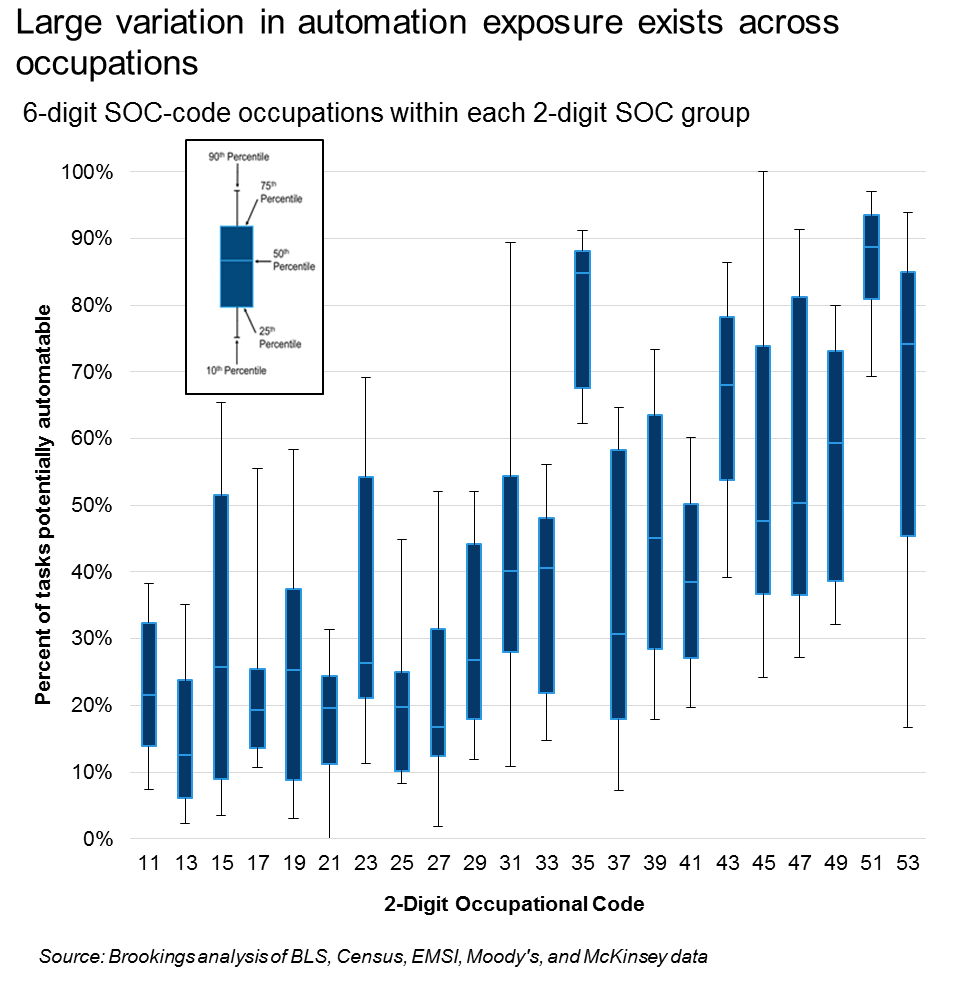
* non-routine “abstract manual” activities (perception, manipulation, dexterity, physical adaptability)
* creative intelligence (ideation, critical thinking, problem solving)
* social intelligence (intuition, teamwork, persuasion, situational adaptability, perceptiveness, caring for others)[[34]](#endnote-34)

Given that, tasks that involve information collection and processing or the performance of physical activities and operating machinery in predictable physical environments will be more vulnerable to new digital technologies. These activities are prevalent in many middle-skill roles—including office administration, construction, maintenance, repair, production, and transportation, and the low-wage manual-intensive areas of food preparation and agricultural activities.

Activities that seem relatively secure, by contrast, include: the management and development of people; applying expertise to decision making, planning and creative tasks; interfacing with people; and the performance of physical activities and operating machinery in unpredictable physical environments. These activities are most prominent in highly skilled management, professional, and technical roles; high, middle and low-skilled roles involving health and personal care or interacting with others; and low-skilled roles that involve cleaning and protective services. Table X below displays some representative occupations and their associated task-level automation potential from McKinsey as utilized by this report, average wages, and educational requirements.



Similarly, Figure X shows the future automation potential of occupations by occupational families (two-digit SOC codes) as derived from the McKinsey ratings. Regardless of whether technological reality will keep up with technological possibility, the pattern of automatability is clear ranging from left to right. Occupations in complex, creative and social fields like management, business and finance, science and technology (computer, math, physical and life sciences, architecture and engineering), law, education, arts, media, and entertainment, health care, and social and community services have among the lowest automation potential across the workforce. At the high end of automation potential, by contrast, are roles in more cut-and-dried activity areas such as office and administration, agriculture, construction and extraction, maintenance and repair, production, transportation, and food services—in general, the areas that saw the most impact in the previous IT era. In the middle are protective services, building and ground maintenance, and personal services.

Note: 11=Management Occupations; 13=Business and Financial Operations Occupations; 15=Computer and Mathematical Occupations; 17=Architecture and Engineering Occupations; 19=Life, Physical, and Social Science Occupations; 21=Community and Social Services Occupations; 23=Legal Occupations; 25=Education, Training, and Library Occupations; 27=Arts, Design, Entertainment, Sports, and Media Occupations; 29=Healthcare Practitioners and Technical Occupations; 31=Healthcare Support Occupations; 33=Protective Service Occupations; 35=Food Preparation and Serving Related Occupations; 37=Building and Grounds Cleaning and Maintenance Occupations; 39=Personal Care and Service Occupations; 41=Sales and Related Occupations; 43=Office and Administrative Support Occupations; 45=Farming, Fishing, and Forestry Occupations; 47=Construction and Extraction Occupations; 49=Installation, Maintenance, and Repair Occupations; 51=Production Occupations; 53=Transportation and Material Moving Occupations

How do these exposures break out as shares of the nation’s employment? The picture seems significant but less than dire at the national level. Figure X shows the distribution employment by task-level automation potential, broken into low (0 to 30 percent), medium (30 to 70 percent), and high potential (70 to 100 percent) groupings.[[35]](#endnote-35)



Over the next few decades, some 25 percent of U.S. employment (36 million jobs in 2016) will have experienced high exposure to automation (with greater than 70 percent of current task content at risk of substitution. At the same, the data suggest that another 36 percent of U.S. employment (52 million jobs in 2016) will experience medium exposure to automation by 2030, while another 39 percent (57 million jobs) will experience low exposure.

That one-quarter of American jobs will be seriously disrupted is sobering. Yet, it is somewhat reassuring that more than 60 percent of jobs will see only mid-level or low disruption, while just 4 percent of U.S.employment in 2016 (7 million jobs) resides in occupations with greater than 90 percent automation potential in the next two to three decades. Still more reassurance comes from the fact that just half of a percent of the workforce (740,000 people) labor in roles that are 100 percent automatable. In short, much work is going to be quite durable even though very few roles will see no task change as much work is going to evolve—likely at faster rates of change.

**5. The impacts of automation in the coming decades will be variable across occupations, and will be visible especially among lower-wage, lower-education roles in occupations characterized by rote work.**

Looking more closely, automation’s likely future impacts on occupations reflect distinct patterns of labor-market impact.

Figure X illustrates clearly that occupations’ current-task automation potential (moving up the vertical axis) are highest for roles with the lowest wages (to the left on the horizontal axis) and declines as wages rise (toward the right of the figure).



In this regard, it is worthwhile to compare the nearby plot of current-task automation potential with wages with the earlier one displaying the 1980 relationship of routine task-intensity and wage percentiles. Whereas before routine task content below the 20th wage percentile was low, here the highest potential for future automation of current tasks is concentrated among the lowest wage earners, reflecting increased projected inroads of automation into the large service sector. Task-level automation potential, meanwhile, falls steadily as average wages rise. Higher earners for the most part continue to face low automation threats based on current task content—though that could change as AI begins to put pressure on some higher-wage “non-routine” jobs. At least one new research inquiry suggests exactly that.[[36]](#endnote-36)

Undoubtedly, though, it is the changed situation of occupations in the bottom third of the wage distribution that stands out as change in the impacts of IT and AI era automation. Some occupations with relatively low routine task-intensity—bus and taxi drivers, wait staff, carpenters, electricians—and that consequently were relatively immune to tech-driven automation over the last 30 years, now have the potential to see significant change in their task composition. This implies a shift in the composition of the low-wage workforce toward occupations for which automation remains a more distant prospect, like protective services, personal care work, or building maintenance and groundskeeping.



With that said, lower-pay occupations requiring less than a bachelor’s degree for entry, including both low- and middle-skill job areas, will still for the most part face the greatest chance of workplace activity change in the coming decades. Many of the most routine- and manually-oriented roles in production and office administration will also continue to require less and less human involvement. The average automation potential of occupations requiring less than a bachelor’s degree is 55 percent, more than double the 24 percent susceptibility among occupations requiring at least a bachelor’s degree. Given this pattern, occupational groups like food preparation and serving, production, and administrative support—paying wages of only 50 to 75 percent of the national average—could experience current task-level disruption in excess of 60 percent and ranging up to 80 percent. By contrast, occupations that require higher levels of educational attainment, such as business and financial operations or engineering, which pay more than 150 percent of the average wage, will see as little as just 14 percent of their current tasks be displaced by automation.

Similar results surface when looking at the average automation potential of *workers* by actual educational attainment, rather than the estimated educational requirements of the roles they inhabit. By that measure, workers without a bachelor’s degree are on average employed in jobs with task automation potential of 49 percent. Some 29 percent of such workers are currently employed in jobs with an current-task automation potential over 70 percent. These estimates differ markedly from those for workers with at least a bachelor’s degree, whose jobs have an average automation potential of only 29 percent. What is more, just 6 percent of workers with a four-year degree or more are employed in jobs with high potential for disruption.



Turning to industries, automation potential is highest among primary and secondary activities such as manufacturing, agriculture, and mining as well as in some large service sectors such as retail and food preparation. The inclusion of the latter again points to the main difference between AI and IT era automation, namely, that such low-wage service activities have in recent decades absorbed employment shifted into them from industries that are more reliant on routine-intensive labor. Now, though, automration risk could reach as high as 73 percent of the current task content of today’s occupations in accommodations and food services, followed by 59 percent in manufacturing and 58 percent in transportation and warehousing. The self-checkout kiosk and AI concierge may soon loom just as large as industrial robots as threats to future employment. By contrast, the risk of task substitution is less than half that in high-skill, complex, and interpersonal industries like information, management, professional and technical services, and education.



Similarly, a recent academic study that looked at automation over 35 years across these industries in 19 advanced economies found higher levels of automation in primary, secondary, and trade and transport activities with lower automation risk in services.[[37]](#endnote-37) In the automated industries, this had the effect of increasing productivity and decreasing employment, while shifting employment into less-automated areas. In a similar vein, we also observe a slightly negative relationship between the size of industries in terms of employment—as well as their pace of growth in the last 16 years—and their automation potential. In other words, excepting the one outlier of food and accommodation services, current-task disruption looks like it will be be greatest in the industries that now employ some of the fewest workers as a result of sustained productivity growth. At the same time, lesser task disruption can be expected in a number of large service industries characterized by a social- and personal-care orientation and low productivity growth.

Put all of this together, and it may be that the experience of automation among industries in the future will be similar to the experience of the most recent few decades: Several segments of the economy—manufacturing, logistics, food service—are poised to experience higher automation, increases in productivity, and reduced employment, while others—health care, education, professional services—experience the opposite. Nevertheless, technological possibility is not technological reality and we are unable to predict how the complex factors such as supply and demand shocks, wage and price adjustments, innovation, and sectoral reallocation will unfold. However, a reasonable assessment of the data points more toward a basic continuity than a dramatic departure from the past.

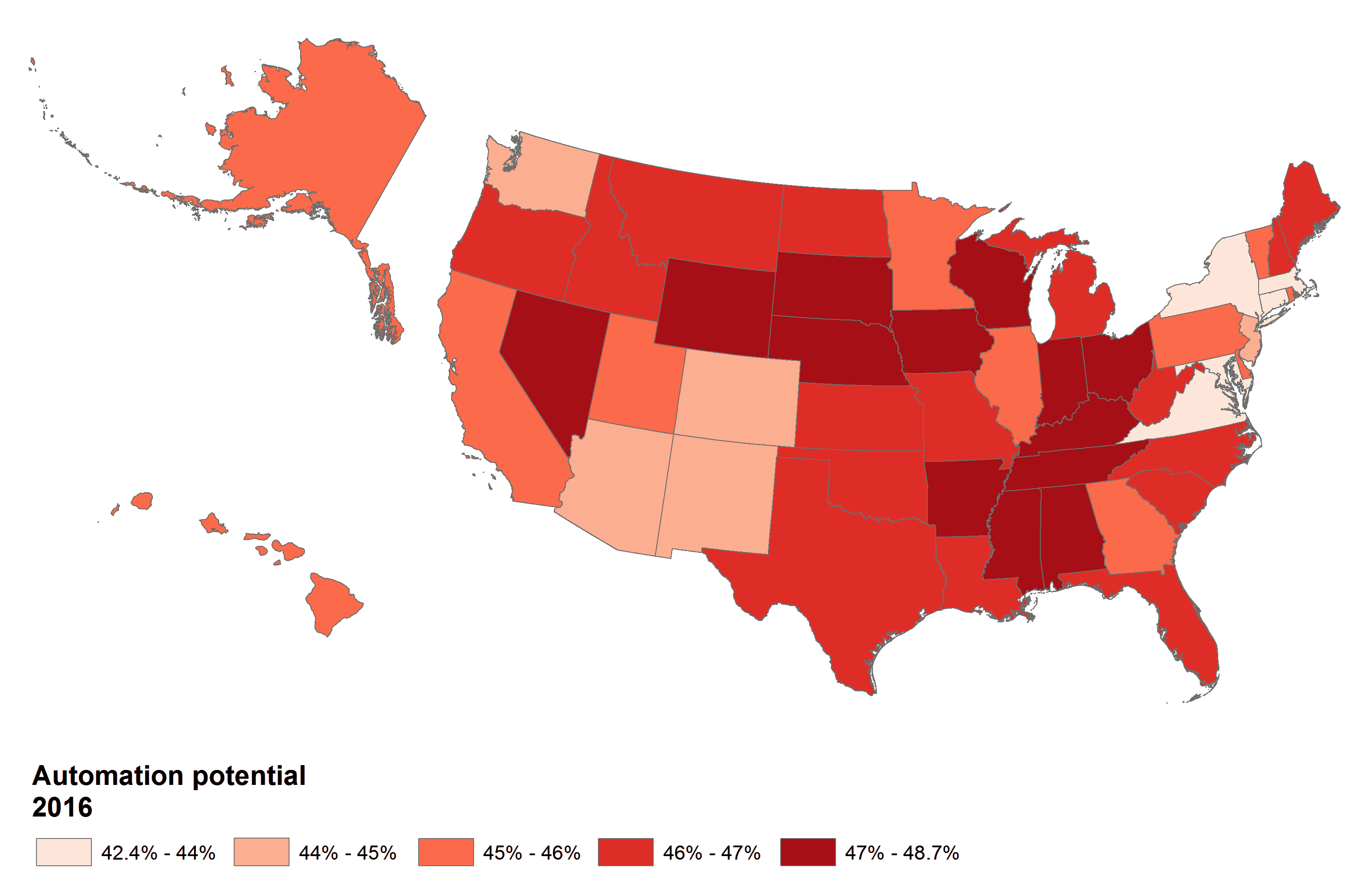
**6. Automation risk varies across U.S. regions and states but it will be most disruptive in Heartland states—the same region hit hardest by the IT era.**

While automation is likely to continue to take place everywhere, its inroads will be felt differently across place. This is true because local automation risks vary with the local industry, task, and skill mix, which in turn determines local susceptibility to task change (along with variances in adoption, which is a factor we cannot account for here).

Large regions and whole states—which contain less distinct industrial compositions than smaller locales like metropolitan areas—contain noticeable but not in most cases radical variations in current task exposure to emerging technologies. Compounding this that one of the most unbiquitous industries—food and accommodation services—is an outlier in terms of high automation potential.

Along these lines, the state-by-state variation of automation potential is relatively narrow, and ranges from 48.7 and 48.4 percent of the employment-weighted task load in **Indiana** and **Kentucky** to 42.9 and 42.4 percent in **Massachusetts** and **New York,** as is depicted in Figure X:

**Average automation potential by state, 2016**



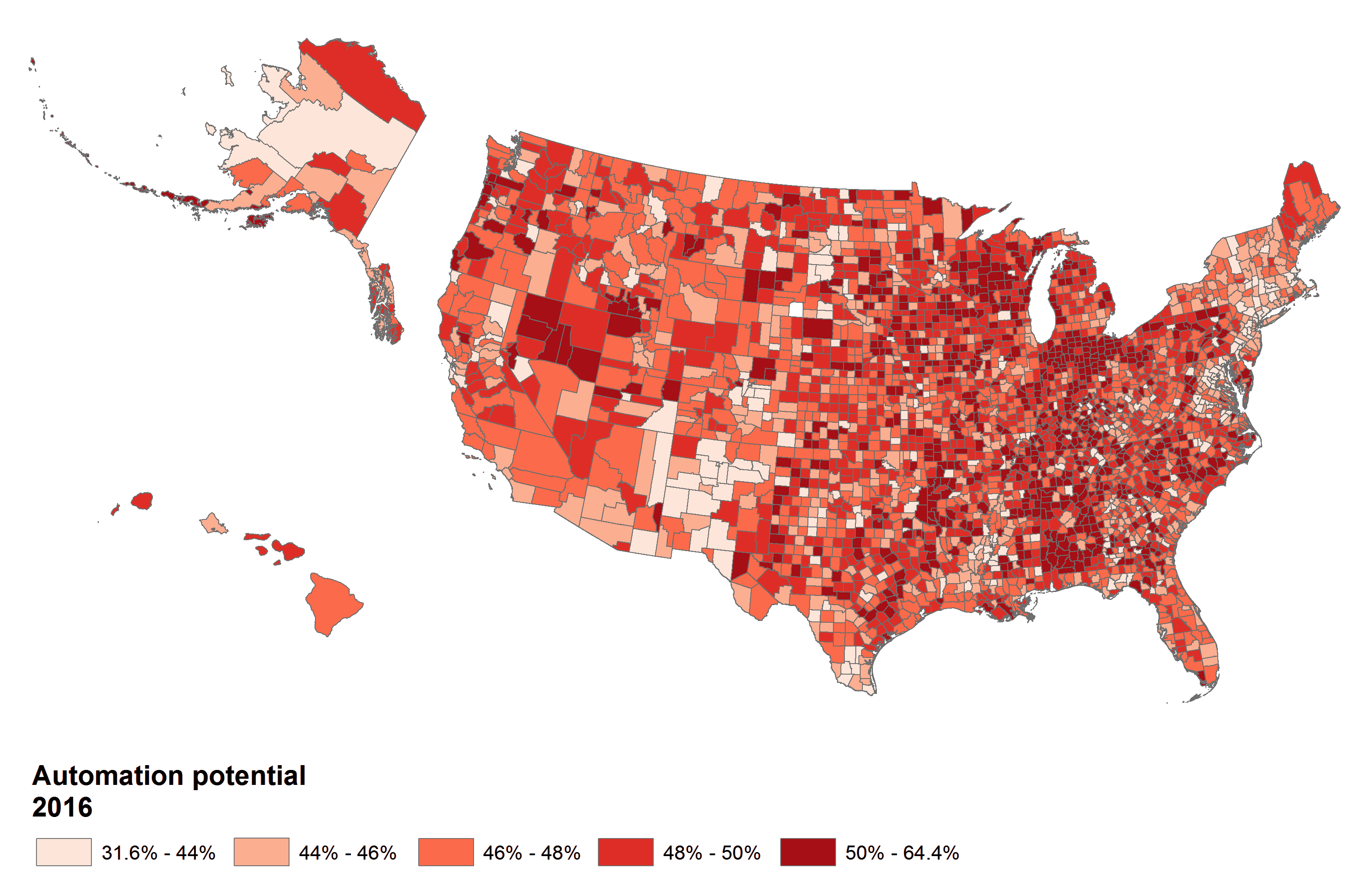
*Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data*

Yet, the map of state automation exposure is distinctive and suggestive. Overall, the 19 states that the Walton Family Foundation labels as the American Heartland have an average employment-weighted automation potential of current task content at 47 percent, compared with 45 percent in the rest of the country.[[38]](#endnote-38) It bears noting, in addition, that the Heartland states encompass many of the commuting zones that contained the highest concentrations of routine employment in 1980. Much of this region then and now specializes in manufacturing and agricultural industries.

As expected, this state-by-state story tracks closely with educational outcomes and industry composition. Less than one-quarter of adults in **Kentucky**, **Arkansas**, **Alabama**, and **Mississippi** have a bachelor’s degree or more, ensuring that all four states face automation exposures of current tasks in excess of 47 percent. In keeping with that, roughly 40 percent of the employment in these states resides in the industry groups most at risk from automation—accommodation and food services, manufacturing, transportation, agriculture, retail, and mining. Less than one-fifth of the workforce in these states labors in the sorts of jobs we have identified as using digital technologies most intensively.[[39]](#endnote-39) In contrast, states like Massachusetts, **Maryland**, and **Connecticut—**all with bachelor’s degree attainment levels in excesss of 38 percent—turn out to have to have significantly lower automation exposures of 44 percent or less.

This connection is even clearer when the incidence of automation exposure is disaggregated to assess county-level impacts. At this geography, northern Ohio and Indiana, Wisconsin, as well as the Upland South all stand out as especially exposed to current task disruption from future automation technologies. These regions once again surface due to their large employment shares in routine task-intensive occupations common in the manufacturing and transportation sectors. In places like **Elkhart** and **LaGrange** counties in Indiana or Hart county in Kentucky, upward of half of all area workers are employed in these industries. Rural counties with large mining operations, especially in the intermountain West, also figure to be major sites of disruption on the county map of automation potential. By the same token, exposure levels along the **Boston-Washington** corridor and along the West coast appear relatively muted.

**Average automation potential by county, 2016**



*Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data*

In short, many places that contended with significant dislocation from IT-era automation in sectors like manufacturing and transportation during last several decades can anticipate more of it. Most notably, the automation of the nation’s manufacturing core—running from the Great Lakes south to the Gulf of Mexico—is in no way completed. The region still stands to be the most heavily impacted by the adoption of AI age technologies. At the same time, the future of automation looks notably different from how it earlier unfolded in the large urban conglomerations in the Northeast and on the West Coast. There, the future threat of automation looks relatively less severe than the stress that occurred during the recent IT era.

**7. Smaller less-educated communities will struggle relatively more with automation, while larger cities will experience less disruption.**

Looking at the community level, the data reveal more pronounced variation.[[40]](#endnote-40) Overall, smaller more rural communities seem significantly more exposed to the automation of current-task content than larger ones, with communities’ employment-weighted average automation potential generally rising as their population declines.

To show this, Figure X shows the level of automation exposure for six types of counties, arrayed by the size and urban classification of their local communities.

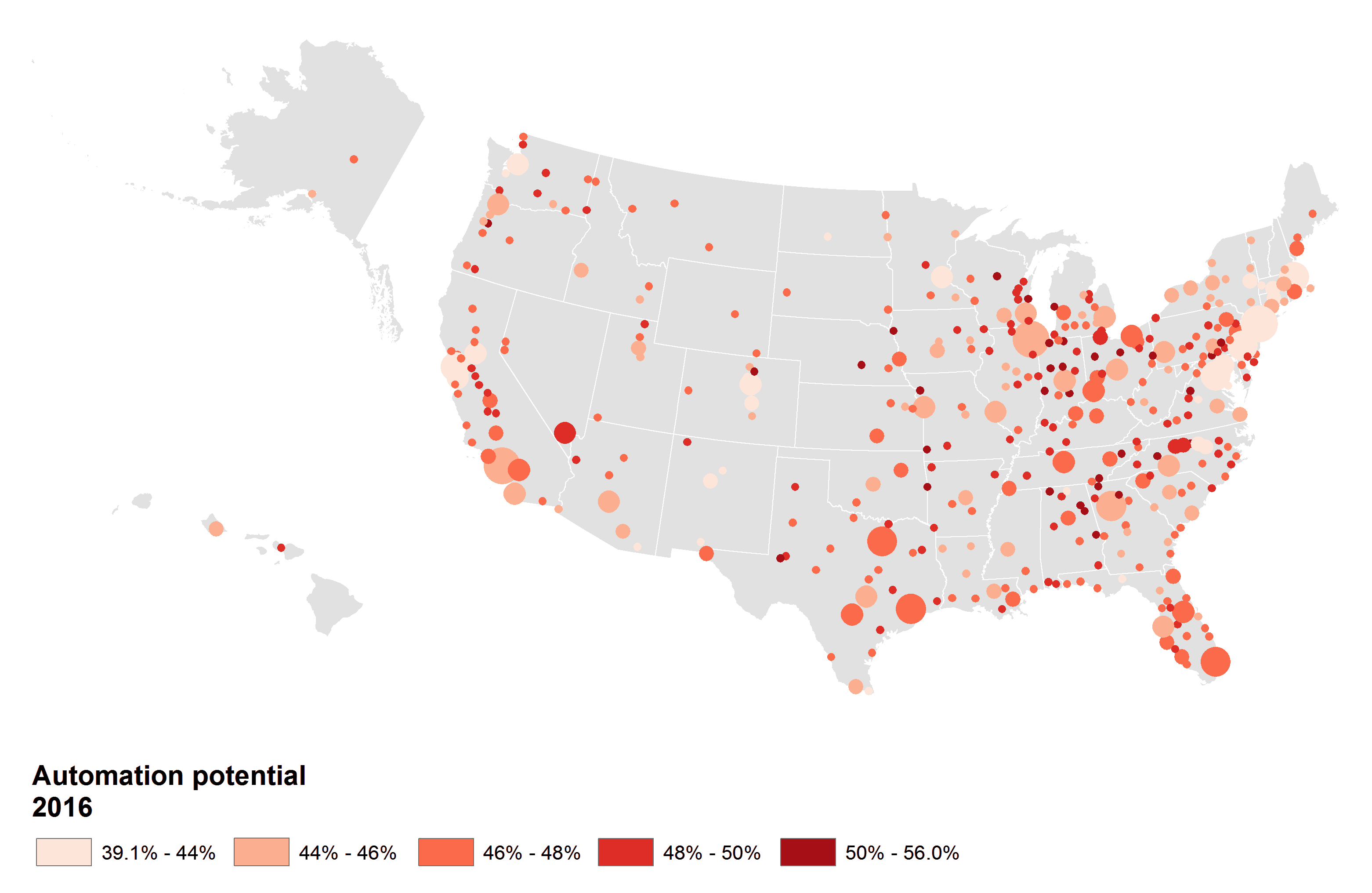


Right off, the figure displays that in general, current-task automation potential declines for counties as population rises, with only the most thinly populated counties being the exception. Roughly three-quarters of all counties in metropolitan areas have on average lower automation exposure than the median rural county. In other words, smaller communities in general face much higher automation risks of current workplace activities than do large ones.

This relationship holds when restricting our focus to just metro areas as well. The average worker in a small metro area with a population of less than 250,000 is employed in a job where 48 percent of current tasks are potentially automatable. While still lower than the 50 percent exposure of rural areas, such small metros encompass places like **Kokomo, Ind.** and **Hickory, N.C.,** where over half of workers’ employment-weighted current tasks are potentially automatable. These are places that have historically specialized in routine-intensive production and so were already on the front lines of IT-era industrial tech deployment. By contrast, small metro areas that appear relatively well insulated from automation are university towns like **Charlottesville, Va.** and **Ithaca, N.Y.,** or state capitals like **Bismarck, N.D.** or **Santa Fe, N.M.**

As to how this plays out across the 100 largest metropolitan areas, it is also clear that while the risk of current-task automation will be widely distributed, it won’t be evenly spread. Among this subset of key metro areas, educational attainment will prove decisive in shaping how local labor markets may be affected by AI-age technological developments. Among the large metro areas, employment-weighted task risk to 2030 ranges from 50 percent and 49 percent in **Toledo, Ohio** and **Greensboro-High Point, N.C.** at the top, to just 40 percent and 39 percent in **San Jose, Calif.** and **Washington, D.C.**

**Average automation potential by metropolitan area, 2016**



*Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data*

Following Washington, D.C. and San Joseamong the larger metros with the lowest current-task automation risk comes a “who’s who” of well-educated and technology-oriented centers including **New York**; **Durham-Chapel Hill, N.C.**;and **Boston**—all with average current-task risks below 43 percent. These metro areas are gaining a measure of resilience from specializations in relatively durable professional, businesss, and financial services occupations combined with relatively large education and health presence. In these metro areas no more than one-fifth of current occupations are 70 percent automatable. By contrast, the average current-task risk in highly susceptible places like **Lakeland-Winter Haven, Fla.**; **Stockton-Lodi, Calif.**;and **Winston-Salem, N.C.** exceeds 48 percent. In these metro areas, over 28 percent of jobs are in occupations that are at least 70 percent automatable under the current task mix. Overall, these places are especially susceptible to change in task content as they contain high concentrations of workers engaged in routine or predictable middle-skill activities, including in the large service sectors of cities dedicated to administration, retail, accomodations, and food preparation.



Overall, higher metropolitan education levels serve as a stay against automation potential—in part because education supports complex interpersonal work and in part because educational attainment improves individual and city adaptability in the face of shocks.[[41]](#endnote-41) The present automation data fits that story. As is visible in the nearby scatterplot, the higher a metro area’s share of workers with at least a bachelor’s degree (2016) the lower is its share of employment in high-risk occupations—meaning those roles with at least 70 percent of their current tasks being automatable in the future. Highly educated metros like Washington, D.C. and San Jose, Calif. have some of the lowest shares of their employment slotted into occupations with high automation risk, while metros with low educational attainment like Stockton, Calif.; Lakeland, Fla.; and **Las Vegas** have as much as twice as much of their workforce in occupations that may be poised for the most significant disruption.



**8. The gravest disruptions from automation in the coming decades will affect men, young workers, and underrepresented groups.**

There is one more compelling set of variations in the way automation may affect society and the economy. These variations reflect the fact that just as automation’s disparate effects are going to pressure particular jobs, industries, and places, they are also going to affect demographic groups in different ways.

, The sharp segmentation of the labor market by gender, age, and racial-ethnic identity ensures that some demographic groups are likely to bear more of the burden of adjusting to AI-age technologies in the workplace than will others.

The probable divides are sharp: Men, young workers, and underrepresented groups all appear likely to face significantly more acute challenges from automation in the next phase than do women, prime-age workers, and whites.



Male workers, to begin with, appear noticeably more vulnerable to potential future automation than women. Such overexposure reflects the fact than men are significantly overrepresented in occupations with higher automation risk of current tasks.

Men, for example, make up over 70 percent of production occupations, over 80 percent of transportation occupations, and over 90 percent of construction and installation occupations—all occupational groups with current tasks loads that have above-average projected automation exposure, though in the case of construction, only slightly. By contrast, women comprise upward of 70 percent of the labor force in relatively safe occupations, such as health care, personal services, and education occupations–all of which encompass positions with relatively lower automation risk.

The result is that in aggregate, men may face slightly more change in the future labor market than women. The average male worker occupies a job where 42.6 percent of current tasks are automatable, whereas women’s jobs face an average automation potential of current tasks of 39.6 percent. Overall, 23.7 percent of male workers hold jobs that are at potential high risk from automation compared to 17 percent of women. With that said, one exception to male automation exposure is the office and administrative support occupation group, where the current-task automation potential of the average occupation stands at 60 percent. Women are significantly overrepresented in such jobs, making up 70 percent of the country’s clerical and administrative workforce. They will, in that domain, face significant change driven by the adoption of more and more sophisticated software and AI tools at the enterprise level.

Automation exposure will vary even more sharply across age groups, with the young facing more disruption. While prime-age workers—those ages 25 to 54—have an average current-task automation potential of 40 percent in the next few decades, that same figure for young workers between the ages of 16 and 24 is 49 percent. Older workers look much more like their mid-career counterparts with workers age 55 to 64 and those 65 and older seeing average automation potential of current tasks of 41 percent and 40 percent, respectively. Nearly 30 percent of young workers are in high risk jobs with over 70 percent of current task content automatable.

This sharp disparity by age makes sense in light of younger workers’ dramatic overrepresentation in highly automatable jobs associated with food preparation and serving: While those ages 16 to 24 make up slightly more than 9 percent of the national workforce, they represent over 29 percent of workers in food prep and service. Nearly half—48 percent—of young workers (those under 25) are employed in the six occupation groups where average automation potential of current tasks exceeds 50 percent (just 34 percent of prime-age workers, on the other hand, occupy such positions). Young workers’ concentration in low-wage food prep jobs is especially concerning given that this large occupation group was relatively unaffected by IT age automation, but now is projected to see as much as 80 percent task change in the coming decades.



Equally sharp variation can be forecasted in the automation inroads that various racial and ethnic groups will face. Hispanic and black workers, for example, face average current-task automation potentials of 47 percent and 44 percent for their jobs, figures well above those likely for their white (40 percent) and Asian (39 percent) counterparts.

Underlying these differences is the stark over- and underrepresentation of racial and ethnic groups in particular occupational families that face elevated exposure to current-task automation. Hispanic workers, for instance, account for 15.5 percent of the American labor force and yet represent 32.6 percent of the workforce in construction and extraction trades. These are jobs that on average could see half of their current tasks automated in the AI-era. By contrast, less than 10 percent of education or managerial jobs are performed by Hispanic workers. Black workers’ slightly lower average automation potential is accounted for by their overrepresentation in health care support and protective and personal care services, jobs which on average have under 40 percent current-task automation susceptibility.

These demographic trends make plain the imperative to embrace proactive labor market interventions to assist workers in nimbly responding to any potential disruptive shifts in employment demand or skill requirements. Otherwise, the promise of AI era technologies to drive future growth in the American economy could be undermined by their potential to worsen existing inequalities on the basis of gender, age, educational attainment, and race.

5. Implications: Strategies for adjusting

Automation will continue to reshape the work people do and the opportunities they are afforded. Whether this should be alarming or only cause for a little anxiety depends.

So while our analysis shows the next phase of the automation era may not be as dystopian as the most dire voices claim, plenty of people and places will be hurt, and much will need to be done to mitigate the coming stresses.

Fourmajor agendas require attention as the nation moves into the AI period of automation.

To start with, government must work with the private sector to **embrace growth and technology** to keep living standards high and maintain or increase hiring.

Beyond that, all parties must invest more thought and effort into ensuring that the labor market works better for people. In this manner, firms, industry associations, educational organizations, and governments must work more urgently with workers, students, and others to **promote a constant learning mindset**, **facilitate smoother transitions**, **reduce hardships for individuals who are struggling**, and **help communities that are being heavily impacted mitigate harsh local impacts**. All in all, the nation needs to overhaul what it has not done well in the past.

## **Embrace growth and technology**

One response to the trends detailed here might seem to be to curb technology-driven change. Leaders should resist this impulse. Instead, while committing to a just and beneficial transition, they should embrace tech and indeed automation to generate the economic productivity needed to increase both living standards and the demand for labor in non-automated tasks. By embracing technology-based growth the nation and its regions will have the best shot at ensuring that there are enough jobs.

Which is why the nation needs to focus more attention on maintaining a full-employment economy both as a direct policy goal and as a crucial benefit of spurring technology-based economic development. Along those lines, policymakers and economic development leaders should respond to the coming next phase of the automation revolution with a renewed focus on job-creation.

Specifically they should:

* run a full-employment economy, both nationally and regionally
* embrace transformative technology to power growth

**Run a full-employment economy, both nationally and regionally**

Numerous analysts agree that one of the most fundamental policy priorities going forward must be to run a full-employment economy.[[42]](#endnote-42) In conditions of widespread hiring, after all, workers will have an easier time of maintaining employment or transitioning from one job to another—a critical need in the coming automation era.

The problem is that over the last three-plus decades the U.S. job market has spent much more time above than below the unemployment rate associated with full employment, meaning there has been a lot of slack in the job market.[[43]](#endnote-43)

As a result, wages have stagnated and income inequality has grown. What’s needed is more demand, including for those displaced by automation.

Which is why many have argued that the federal government should **appoint Federal Reserve governors who focus more on full employment** than on fighting inflation.[[44]](#endnote-44) A full-employment economy, both national and regional, will help minimize the dislocations associated with the next rounds of automation.[[45]](#endnote-45) Adjustment and reemployment will proceed far more smoothly if there are plentiful job openings, after all.

However, broad monetary policy is a necessary but, by itself, insufficient tool for bringing full employment to every area. Also essential, as argues Josh Bivens of the Economic Policy Institute (EPI), are public policies that aim to extend job-creation into areas of elevated unemployment and promote job intensity across the economy.[[46]](#endnote-46) Along these lines, governments should **boost job creation through public investment** in areas of need such as infrastructure, affordable housing, and early childhood care. Also, the public sector could **increase the job yield of such public investments** by limiting the hours of individual jobs and maximizing leave and vacations.

**Embrace transformative technology to power growth**

Policymakers in the automation era must expand their focus beyond generic job creation (though that does matter) by placing tech-driven productivity gains at the center of their growth strategy.

Productivity growth is essential to increasing living standards. High-productivity firms generate more output per worker, which in turn allows them to reduce prices, increase market share, and pay better salaries. But more relevant to automation are what economists Daron Acemoglu and Pascual Restrepo call the “productivity effects” of automation.[[47]](#endnote-47) The productivity effect—resulting from the cost savings generated by automation—increases demand for work and wages in new or non-automated tasks. These effects push directly against the “displacement effects” of technology, which tend to reduce the demand for labor.

And so a second major aspect of an automation-resilient employment strategy must be strong initiatives to support the development and wide adoption of transformative technologies that catalyze innovation, drive productivity growth, and ultimately support job creation.

A number of such initiatives are outlined in Brookings’s recent reports focused on agendas for boosting America’s high-productivity advanced industries and deepening the nation’s digital skills to support high-tech growth.[[48]](#endnote-48) Each of these call for aggressive “bottom-up” strategy-setting and initiative delivery at the regional level combined with expanded state and federal investments in innovation and skills-development. Such initiatives will only become more important as AI gains sway and the demand for job-creation sharpens.

Beyond those frameworks, the dawning of the intelligent age requires specific efforts focused on the development and diffusion of automation and AI. First, the federal government needs to **increase R&D funding on AI, automation, and associated technologies** in order to preserve America’s technical edge and ensure these technologies’ effective and humane development. Ceding leadership to China in this area could have grave consequences for U.S. economic growth as well as for the ethical frameworks and standards around automation.[[49]](#endnote-49)

Increasing research investments by the Department of Defense should be complemented by steady support of long-term civilian research on topics like advanced robotics, digital manufacturing, improved design tools, general purpose AI, and enhanced perceptual capabilities in AI systems.[[50]](#endnote-50) Also critical are urgent investments in the development of effective human-AI collaboration; humane and ethical automation and AI; and the legal and societal implications of these technologies.[[51]](#endnote-51) In each case government research can provide a needed offset to private applied research, which may not always prioritize social good.

**The Vector Institute and the Pan-Canadian Artificial Intelligence Strategy**

While the U.S. has struggled to develop a coherent national automation and AI strategy, Canada has launched the type of focused, aggressive response that will be needed to adapt to the AI era. The Vector Institute, based at the University of Toronto, is a centerpiece for AI development in Canada. Its goals are to develop AI for practical, real-life applications and to build a sustainable AI ecosystem in Canada. The Institute also works to enhance technology transfer by supporting Canada’s innovation clusters in AI and helping Canadian start-ups grow to become global leaders.[[52]](#endnote-52) Finally, it aims to generate more Masters and PhD graduates in machine and deep learning than anywhere else in the world.[[53]](#endnote-53)

To date, the institute has received some $100 million in financial support from the government of Canada and the government of Ontario, as well as another $80 million from private industry.[[54]](#endnote-54) Its partnership with the University of Toronto allows it to access top talent in the field, and provides faculty and students the opportunity to develop and commercialize their research.

The Vector Institute is one of three anchor institutions for the broader Pan-Canadian Artificial Intelligence Strategy, along with the Alberta Machine Intelligence Institute (AMII) in Edmonton and the Montreal Institute for Learning Algorithms (MILA). The Pan-Canadian Artificial Intelligence Strategy aims to make Canada a global leader in AI by supporting a national research community on artificial intelligence, developing a skilled national AI workforce, and exploring the economic, ethical, policy, and legal implications of advances in AI.[[55]](#endnote-55)

In sum, the nation can avoid the false dichotomy between automation and employment by maintaining a full-employment economy, both through direct intervention as well as through new automation and AI technologies aimed at maximizing job creation and productivity.

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But the nation and its workers will need more than just a sufficient rate of job creation to offset certain job destruction.

Even if sufficient numbers of jobs are maintained, the growing need for workers to adjust to the changing nature of existing jobs or shift from existing jobs and tasks to new ones will be disruptive. Even in the best of conditions it takes time for workers to develop new skills to secure to jobs in which they can be productive, and as Acemoglu and Restrepo note, layoffs from existing jobs can depress local or national labor markets, further increasing the costs of adjustment. Some workers never quite adjust.

Which is why the nation needs to commit to deepset educational changes, new efforts to help workers and communities adjust to change, and a more serious commitment to reducing hardships for those who are struggling.

**Promote a constant learning mindset**

The AI era of automation will accelerate many of the labor market trends already in force—in particular the disruptive process of task creation and destruction. This acceleration will require workers to develop a constant learning mindset and use it to work both with machines, and in ways machines cannot. That means workers will need to take a new approach to learning and skills development, and that companies, educational institutions, and governments need to shift to support this change. Five strategies appear urgent:

* Invest in reskilling incumbent workers
* Expand accelerated learning and certifications
* Make skill development more financially accessible
* Align and expand traditional education
* Foster uniquely human qualities

**Invest in reskilling incumbent workers**

Change will most naturally and urgently begin within companies, where firms and their existing workers will mutually experience the need for skills changes. An important starting point therefore will be to **increase the prevalence of employer-led training**.

While the conventional wisdom says that employees, not companies, are the primary beneficiaries of training, in fact, a variety of empirical studies have shown that firms frequently recapture the costs of training workers, in particular through increased worker productivity.[[56]](#endnote-56) Employer-led trainings can improve firm output, enhance workers’ career prospects, and help companies fill emerging critical needs.[[57]](#endnote-57) Unfortunately, businesses today are less likely than in the past to offer access to on-the-job training or financial support for upskilling.[[58]](#endnote-58) Firms should reconsider their hesitation.

Likewise, a well-structured program that builds time for training into workers’ shifts can help alleviate many of the barriers that workers face.[[59]](#endnote-59) In this regard, more firms should leverage the emergence of new models, such as unbundled online courses, that allow firms and workers to craft curricula to target the skills that they deem most relevant.[[60]](#endnote-60)

**Expand accelerated learning and certifications**

Training and education can benefit, meanwhile, from ongoing experiments in accelerated and competency-based learning models, which will become more important as automation and AI accelerate the extent and pace of task change in many jobs. These changes will sharpen the need for workers to rapidly acquire and effectively signal to employers what skills they possess.

As education and training become a lifetime endeavor, rapid learning in concentrated disaggregated formats will play a growing role. To better facilitate this shift, businesses, educational institutions, governments, and non-profit organizations should work to **refine and scale up emerging models for accelerated learning** such as tech “boot camps” and coding schools—including into domains far beyond the immediate tech sector. To achieve this, new collaborations are going to be needed to work out compelling use cases and business models. This will be particularly important in a sector that has seen a proliferation of new course providers, but has also faced criticism over organizational closures, high costs, and relative lack of information about student outcomes. Promising, albeit narrow, efforts are underway. Some cities and states have tried to establish their own publicly available accelerated learning programs.[[61]](#endnote-61) These efforts are running in parallel to federal efforts to benchmark new educational funding models, including for accelerated learning.[[62]](#endnote-62) In other instances, companies are working with providers to shift the cost burden away from learners.

**Accelerated learning as end-to-end talent development**

In one of the most promising models, some accelerated learning providers have refashioned themselves as end-to-end talent developers. LaunchCode, a non-profit coding school, helps firms identify prospective employees, and then upskills them through a coding boot camp at no charge to the worker. Upon graduation, a worker is placed in an apprenticeship at one of LaunchCode’s 500 partner firms.[[63]](#endnote-63) Similarly, General Assembly, a for-profit coding school, has developed a talent pipeline service, helping firms to assess the digital skills of their workforce, and upskill, reskill, or recruit and train new talent to fill institutional needs.[[64]](#endnote-64) This model not only takes the cost burden off of individual workers, but also facilitates stronger training-to-employment pipelines. Government agencies should explore how best to leverage this model, in particular to encourage training for more women, minorities, and low-income individuals.

As the market for accelerated learning continues to expand, companies will need to be able to effectively evaluate which skills workers have mastered. Therefore, state and local governments, in partnership with industry associations, business services groups, and other employer intermediaries, should **develop and push wide acceptance of skill-based hiring**.[[65]](#endnote-65) This would stand in contrast to current standard hiring practices, which designate a high school diploma or university degree as the primary, and often sole, credential. Skill-based hiring efforts could in turn be leveraged to facilitate “stackable credentials” by laying out which skills and certifications can be combined into the equivalent of a degree. State and local governments, for their part, should work to synchronize standards for credentials in order to better enable workers to move to areas of strong industry demand.[[66]](#endnote-66)

**Make skill development more financially accessible**

As the need for constant skill development rises, more workers will struggle to pay for that learning on their own. Which is why policymakers should work to not only combat the decline in employer-sponsored training but also to help workers finance their own skill development.

Although firms frequently recapture the costs of training workers, companies remain hesitant to invest, leading to suboptimal training investment throughout the economy.[[67]](#endnote-67) To reverse this trend, governments should **incentivize on-the-job training and tuition assistance**, for example through a tax credit for new training initiatives, akin to the federal Research & Development Tax Credit.[[68]](#endnote-68) While recent federal efforts to establish a training tax credit have failed, several states, including Connecticut, Georgia, Kentucky, Mississippi, Rhode Island, and Virginia, have their own.[[69]](#endnote-69)

However on-the-job training will not always be available, and high prices for many forms of education and training has made lifelong learning an expensive proposition. Accordingly, policymakers must work to not only expand opportunities for on-the-job skill development, but also make it easier for workers to help themselves. One way to do so is to **establish portable lifelong learning accounts (LiLAs)** to better facilitate workers’ constant learning. With LiLAs, employers, workers themselves, and, in some circumstances, the state, contribute to a tax-advantaged account that workers use to direct their own skill development and that stays with the worker regardless of employer.[[70]](#endnote-70) States and the federal government should give tax preferred treatment to such programs. In order to prevent the benefits from flowing disproportionately to higher-income workers, governments shouldmake direct contributions to the accounts of low-income workers.[[71]](#endnote-71) Beyond LiLAs, another way to help workers finance their own skill development is to **allow financial aid to cover more forms of education**, for example by providing access to Pell Grants and federal loans for programs such as short-term certificates through community colleges or other educational institutions.[[72]](#endnote-72)

**Align and expand traditional education**

Yet, automation and AI will demand still deeper-going change. To develop a workforce prepared for the changes that are coming, educational institutions must deemphasize rote skills, and stress education that helps humans to work better *with* machines—and do what machines can’t. This means more focus on developing students’ digital skills, as well as an increased emphasis on experiential learning.

Digital, statistical, and other technical skills are increasingly essential to ensure successful collaboration with technology—and employment resilience. Already high- or mid-level digital skills are virtually required to secure above-median income jobs.[[73]](#endnote-73) Likewise, digital skills can also help workers collaborate better with technology, thus reducing the share of a job’s tasks that are susceptible to future automation.[[74]](#endnote-74) This makes digital skills prerequisites for durable employment in the AI era.

In view of this, colleges and universities should make digital skills central to all students’ education. This begins by working to **incorporate digital skills development into general education requirements** to ensure all students get at least some digital exposure. An important complement to this will surely be to encourage tech minors for all students, regardless of field of study.[[75]](#endnote-75) But simple exposure to digital skills will not enough to prevent attrition. Colleges and universities must also **overhaul curricula in computer science and related fields** to increase real-world context.[[76]](#endnote-76) In this regard, expanded course offerings in hard-core technical fields like computer, data, and cognitive science will grow in importance, but so will course offerings that allow students—in the spirit of preparing people to work with machines—to marry humanistic study with technical training.[[77]](#endnote-77)

For their part, community colleges should **expand digital offerings to upskill workers without degrees**. Digital skills can be essential “door openers,” in particular for less educated workers who are in the type of rote lower-wage roles that are most vulnerable to automation. For some workers, mastery of productivity software such as Microsoft Excel or Salesforce will be sufficient. Others will need exposure to more specific software, such as digital design programs or health care billing platforms. Community colleges should strengthen connections with local tech communities to quickly scale up training for software in demand in the regional economy.[[78]](#endnote-78)

At the K-12 level, one of the most important actions that policymakers at the federal, state, and district level can take is to **incorporate computer science (CS) education into school curricula**, particularly in high schools. This will help disseminate the baseline digital skills that workers will need to work with machines to the broadest array of students. Currently only about 40 percent of U.S. K-12 schools teach computer programming.[[79]](#endnote-79) Schools should also update how digital skills are taught by leveraging programs such as Hour of Code to make CS fun and relatable to a variety of students. Beyond CS, K-12 schools will need to pivot coursework in other fields. For example, high schools should place less emphasis on so-called continuous math such as advanced calculus, and instead prioritize applied math such as statistics, which is relevant for more workers.[[80]](#endnote-80)

Across all levels, educational institutions must make a greater effort to **foster a sense of community for women and minorities studying tech**. Just 18 percent of computer science graduates are women, while fewer than 10 percent are Latino and only 5 percent are black.[[81]](#endnote-81) As a result, these groups have a low presence in key tech occupations.[[82]](#endnote-82) Efforts should begin in K-12, with programs such as workshops and field trips focused on encouraging individuals to get involved in tech. From there, students at all levels should be supported through formal mentorship programs and informal networks.[[83]](#endnote-83)

In addition to enhancing students’ digital skills, one of the best ways that educational institutions can help prepare for a more automated economy is to **expose students to more experiential learning**. Experiential learning, in which students mix classroom learning with non-rote real-world experience, develops qualities like creativity, mental flexibility, and cultural agility that are unlikely to be automated and are necessary to solve the types of problems that machines cannot.[[84]](#endnote-84) One of the most effective ways for colleges and universities to increase the prevalence of experiential learning is to make better use of co-ops and paid internships, integrating students’ work experiences with their on-campus learning.[[85]](#endnote-85) Colleges and universities should also use more on-campus experiential learning such as project-based learning and new methods such as “serious games” that help students develop the same skills in creativity and mental flexibility.[[86]](#endnote-86)

For individuals not enrolled in a four-year college or university, apprenticeships can help develop a similar set of skills. Industry associations and firms should therefore develop models to **leverage apprenticeships in more industries** such as health care, finance, and other service industries. Apprenticeships also have the important additional benefit of providing access to a post-secondary credential for workers who do not have a four-year college degree.

K-12 schools should work to increase their own use of experiential learning. Schools at both the elementary and high school level would do well to utilize more project-based learning, with a focus on fostering problem-solving, collaboration, teamwork, and social perceptiveness. Schools can also experiment with school-business partnerships, particularly to give high school students direct exposure to industries of interest.

Helping students adapt to the impacts of automation will need to start, for that matter, even before a child begins kindergarten. More states and municipalitiesshould **establish universal pre-kindergarten programs**, and the federal government should support these efforts. Early childhood education is important because it puts a strong focus on the so-called “soft” skills such as creative thinking and curiosity that will be essential to doing the type of work that machines cannot.[[87]](#endnote-87) Individuals who receive exposure to these skills from an early age are better prepared to cultivate them throughout their lives. However, in 2016, only 54 percent of children ages 3-4 had access to pre-school in the U.S., and access to early childhood education varied significantly along racial and socioeconomic lines, with minority and low-income children at a significant disadvantage.[[88]](#endnote-88)

**Foster uniquely human qualities**

In all of this, finally, the age of brilliant machines means humans must focus on “what we are that computers aren’t,” as Andrew McAfee and Erik Brynjolfsson write.[[89]](#endnote-89) This is going to require a new, more rigorous focus on the “soft” or “human” skills mentioned above.[[90]](#endnote-90)

What does this mean? As digital automation and AI substitute for more and more tasks while creating new types of work, workers will need to constantly reorient themselves, reskill, and readjust. That means that individuals, firms, and the overall training and education ecosystem must all **embrace a mindset of adaptability and constant learning**.[[91]](#endnote-91) The rapid progress of AI is going to increasingly take over rote or otherwise predictable tasks, disrupting the content of jobs and creating a constant need to redeploy. Given these changes, the training and education system itself must move beyond rote information sharing to embracing education that encourages persistence and ingenuity, helps people manage transitions, and improves their response to ambiguous challenges.

At the same time, the fact that no skills will be more durable or valuable than human interaction means that all kinds of training and education should **focus on enhancing interpersonal skills and emotional intelligence.** With the machines doing the calculations and more and more of the analysis, human teams will be increasingly important to think across domains, brainstorm the next move, boost morale, work out the ethics, negotiate the deal, and otherwise make choices. At the same time, large swaths of economic activity—from health care and social services to coaching and government and education—will remain durably human and shaped by empathy, tact, and the human touch. Such social skills may well be in greater demand in the near future than narrower technical skills such as programming. The outlines of a human-skills pedagogy for the AI era are already visible in management and education schools.[[92]](#endnote-92) Now they need to be diffused ubiquitously. Long to short, the training and education system will now need to both support learning in new ways, constantly over time, while focusing especially on the uniquely human work the machines cannot do.

## **Facilitate smoother adjustment**

A mindset of constant learning will allow many workers to reskill sufficiently to maintain a place in the AI economy. However, while most workers will only see a portion of their jobs’ task content change, millions of workers toil in jobs that will be eliminated. These “displaced” workers will face a particularly difficult path to reemployment. Once workers are displaced from a job, it often takes a long time for these workers to adjust—to learn about a new industry and occupationand to develop the skills necessary to get hired in a new job.

Exacerbating these difficulties in the United States is the nation’s woefully out of date worker adjustment system, which slows adaption to automation, increases inequality, and reduces the productivity gains from new technology.[[93]](#endnote-93) Today, the most widely used programs that support dislocated workers transition to a new job have their roots in the New Deal of the 1930s—and some of them remain essentially unchanged since their creation.[[94]](#endnote-94) While the technologies impacting American workers have changed, our policies haven’t kept up.

To create an adequate adjustment system, federal, state, and local authorities, as well as the private sector, should embrace two strategies:

* Create a Universal Adjustment Benefit to support all displaced workers
* Maximize hiring through a subsidized employment program

**Create a Universal Adjustment Benefit to support all displaced workers**

What do we mean when we say a worker is “displaced”? Displaced workers are those who have lost their jobs because their workplace eliminated their position, closed, or moved.[[95]](#endnote-95) Because their skills are often made redundant, displaced workers can face particularly severe barriers to being rehired, resulting in longer periods of unemployment and lower pay and fewer benefits upon being rehired. Over the past 30 years automation has displaced millions of workers, particularly in manufacturing. As automation and AI become more prevalent in industries such as accommodation, food services, and transportation, more workers will face the same risk.

Currently, most support for displaced workers comes through the Workforce Innovation and Opportunity Act (WIOA), which provides career services and training.[[96]](#endnote-96) However, not every displaced worker can access WIOA services.[[97]](#endnote-97) Meanwhile, narrow subsets of workers have access to more generous programs, such as the Trade Adjustment Assistance (TAA) program for workers who lose their jobs to international competition. However, these more specialized programs shut out workers displaced by automation.

In order to eliminate inequities and better support workers displaced by automation, the United States should create—to coin a label—a Universal Adjustment Benefit for all displaced workers.[[98]](#endnote-98) Three components would anchor such a program:

* Widely available career counseling
* Effective retraining
* Robust income support

The need for such a program has long been recognized, including in proposals by both the Clinton and Obama administrations.[[99]](#endnote-99) Now it is time to build it.

The first component of a Universal Adjustment Benefit must be creating a robust career counseling program for displaced workers. Career counseling services are relatively inexpensive, and studies show they consistently increase earnings and decrease time spent unemployed.[[100]](#endnote-100) Policymakers therefore should **automatically enroll every displaced worker in career counseling**. Currently, most workers must proactively apply to receive job search assistance, meaning many do not access benefits for which they may be eligible. Additionally, the focus of career counseling should be refined to place more emphasis on identifying and fostering skills relevant for an increasingly automated economy. This includes helping individuals identify existing skills that may be adaptable to new sectors, as well as directing workers to training in skills and industries that are growing in demand and resistant to automation.[[101]](#endnote-101)

The next piece of a Universal Adjustment Benefit must be access to effective accessible worker retraining. As automation continues to change the tasks that occupations require, career counseling alone will not be sufficient to connect some displaced workers with new employment. In those cases, workers will need retraining to learn entirely new skills.

To start, the U.S. should greatly **expand training access for all dislocated workers**, regardless of the cause of dislocation. In FY 2015, only 12 percent of WIOA participants received training services.[[102]](#endnote-102) For comparison, over half of workers enrolled in TAA received training services.[[103]](#endnote-103) These inequalities penalize workers for how they were displaced and leave the U.S. underprepared for future dislocations from automation and AI.

There are also structural and human barriers to effective retraining. Disincentives exist in particular for older displaced workers. Some workers have been out of school for years, and many never attended any sort of higher education.[[104]](#endnote-104) For some workers, the marginal pay difference between a new job and federal disability programs may not be that much.[[105]](#endnote-105) Others may not find available jobs appealing—for example, studies show that some non-college educated men may have an aversion to the shift in jobs demanding “soft skills.”[[106]](#endnote-106)

Policymakers should therefore **link trainings to local employers and the local labor market** so that training can lead to adequately paying jobs that effectively utilize workers’ skills. For many workers, training is only a worthwhile value proposition if there is a clear connection into a sustainable job. Improving these linkages should build off other efforts, such as those refining the mission of community colleges. In some cases, industry-led regional skills alliances can help develop a talent pipeline that multiple firms in a local industry can leverage. This can also help mitigate some of the concerns that companies have about competing firms poaching their workers.[[107]](#endnote-107) When sectoral programs aren’t possible, training should provide workers with 21st century skills—ideally quantitative, digital, or technology-focused. A widely cited study by Jacobson, LaLonde, and Sullivan found that training programs weighted toward quantitative skills significantly enhanced outcomes for workers.[[108]](#endnote-108)

However, neither improved career counseling nor more robust worker retraining will be possible given the current U.S. level of financial support for displaced workers. The United States spends just 0.1 percent of its GDP on “active labor market policies,” the policies other than income support that actively facilitate worker reemployment. As a percentage of GDP, this is less than every country in the OECD other than Mexico, and less than half of what the United States spent in 1985.[[109]](#endnote-109) Policymakers should therefore **increase funding for active labor market policies** and index future appropriations to the growth of the labor forceto prevent the erosion of per capita funding.

In addition to investing more in policies that actively connect workers to jobs, the United States. must also help workers support themselves financially while they are job searching or training. As a result, the third pillar of a Universal Adjustment Benefit must be to **strengthen income support during times of displacement and retraining**. Training is in many cases a full-time commitment. However, current U.S. income supports are insufficient to help workers effectively transition from at-risk to resilient work. Unemployment Insurance (UI), the primary income support program for displaced workers, covers fewer than half of unemployed workers and replaces less than half of their salary on average, with wide variation among states.[[110]](#endnote-110) The length of UI benefits also varies, with some states offering as few as 12 weeks.[[111]](#endnote-111) These policies make it difficult for workers to choose to enter training rather than take the first job that comes their way.

However, some displaced workers get support above-and-beyond what other Americans get. TAA, for example, provides workers in training a “Trade Readjustment Allowance” that kicks in once UI benefits end, giving workers an additional 18 months of financial support. Since workers dislocated through automation cannot access this program they are, in effect, penalized because of the cause of their displacement.

Reforms to the current support system for dislocated workers are essential. As an initial step, all states should offer at least six months of unemployment benefits.[[112]](#endnote-112) Furthermore, the U.S. should extend income support for displaced workers in training to cover the full duration of the program, up to at least two years (as is already done with TAA). Additionally, states should increase the maximum income support threshold and index it to the average wage in the local area.

**Danish flexicurity: Intensive support combined with a duty to work**

Among the Nordic countries, the Danish system of ‘flexicurity’, which combines relatively low employment security with strong active labor market policies and generous income support, has received attention as a potential model for other nations.

How does the Danish system work? When workers are laid off, they must register at a local job center or unemployed insurance fund office. Once they have done so, they can access a variety of skills assessments and job matching tools to determine their next step of employment. In order to keep workers engaged with the labor market, displaced workers receive an “activation offer” after a certain period of unemployment, which they must accept. If they do not, their unemployment benefits are reduced or cancelled. Activation offers can be training or a temporary subsidized job at a public or private employer. Temporary jobs tend to be low-wage work, which incentivizes the employeee to find a job of their own volition.[[113]](#endnote-113)

In addition to job search support and a mandatory activation offer, workers receive generous income support. Unemployment benefits cover up to 90% of a worker’s pre-displacement wage, up to a maximum of 849 kroner (U.S. $130) per day.[[114]](#endnote-114) Workers may receive benefits for up to 24 months in any three-year period.[[115]](#endnote-115) And while fewer than half of unemployed U.S. workers receive unemployment benefits, nearly 80 percent of Danish workers have access to them.[[116]](#endnote-116)

So how does flexicurity hold up? Some 20 percent of the Danish labor force changes jobs in any given year.[[117]](#endnote-117) Despite this, the Danish unemployment rate never broke 8 percent during the Great Recession, compared to an EU-wide unemployment rate of 10.9 percent at its peak.[[118]](#endnote-118) Among the working age population, Denmark has an employment rate of over 74 percent, ahead of both the United States (70 percent) and the EU as a whole (68 percent).[[119]](#endnote-119) Furthermore, achieving these outcomes does not seem to depress worker productivity or entrepreneurial activity. Worker productivity is essentially the same in the U.S. and Denmark, according to the OECD.[[120]](#endnote-120) Meanwhile, Denmark ranks highly on global rankings of entrepreneurship, placing sixth out of 137countries in the 2018 Global Entrepreneurship Index (the U.S. ranked first).[[121]](#endnote-121) Finally, some studies have suggested that combining flexible labor markets with greater employment security like in Denmark fosters greater risk-taking among workers.[[122]](#endnote-122)

Some workers may have skills that do not align with their local labor market, but are in demand elsewhere in the economy. In addition to direct income supports then, policymakers should also better **support workers who are willing to move for a new job**. Most workers do not receive any sort of support to move to areas where there skills may be more valuable. TAA is again an exception, providing workers a relocation reimbursement of up to $1,500, but even that number is insufficient. The cost for a family to move can easily run much higher—from $5,000 to over $12,000.[[123]](#endnote-123) As a result, a report by the Council on Foreign Relations, citing Mihir Desai of Harvard Business School, recommend a refundable tax credit of up to $15,000 for workers willing to move more than 200 miles.[[124]](#endnote-124)

**Maximize hiring through a subsidized employment program**

As noted earlier, adjustment will go better if jobs are plentiful—which is why both effective monetary policy and smart fiscal policy with an eye toward job creation will be critical going forward. However, even then the spread of new forms of automation will exacerbate problems that certain workers already face in finding employment, such as those with disabilities or the long-term unemployed. States should therefore **implement subsidized employment programs** to maximize such workers’ chances of being hired.

Employment subsidy programs have multiple benefits. First and most importantly, studies show they consistently raise earnings and employment among disadvantaged workers. This will be particularly important for workers permanently displaced by automation. The programs also have broader spillover effects, such as reducing use of other public assistance, improving school outcomes among children of workers, lowering criminal justice system involvement among workers and children, and reducing long-term poverty.[[125]](#endnote-125) And having an existing jobs subsidy program in place makes it easier to scale up in periods and localities with high unemployment.

Currently there is an existing federal Work Opportunity Tax Credit (WOTC) available to employers that hire individuals from certain groups that face significant barriers to employment, but a subsidized jobs program is widely seen as more effective.[[126]](#endnote-126) Studies show subsidized jobs programs to be more effective than tax credits at creating net new jobs, as well as incentivizing employers to hire disadvantaged workers. Additionally, a jobs subsidy can be tied to a specific worker rather than an employer. This is particularly important for workers dislocated by automation, given their risk for long-term unemployment and the hardships they face in being rehired. This also makes it easier for states to provide so-called “wraparound services,” such as child care or other employment supports, to further support workers most in need.[[127]](#endnote-127)

## **Reduce hardships for workers who are struggling**

A constant learning mindset, coupled with stronger adjustment initiatives, should enable most workers to manage the next few decades by shifting toward higher-skill, non-routine roles working with the machines or in capacities beyond them. However, as automation and AI continue to substitute for people some workers will inevitably be forced into lower-wage service roles. Workers in such positions face a variety of special hardships. Many of these roles lack basic employee benefits such as health insurance, retirement savings, or paid leave. Others will remain underemployed and need to take on multiple part-time jobs to make ends meet. And still others transition into freelance, contract-based, or “gig” work. Not only do these positions frequently lack benefits, they also largely fall outside the purview of basic worker protections, such as the minimum wage and overtime pay. Income volatility, characterized by wide swings in a workers’ take-home pay throughout the year, is also more severe among low-income workers, particularly those in the service sector.

Leaving workers to fend largely for themselves is not the right way to manage the kinds of changes now underway. In order to best support workers who are struggling in an increasingly automated economy policymakers should pursue two broad strategies:

* Reform and expand income supports for workers in low-paying jobs
* Reduce financial volatility for workers in low-wage jobs

**Reform and expand income supports for workers in low-paying jobs**

High-skill jobs that require creative intelligence and adaptability are likely to both remain impervious to automation and pay a premium. However, the coming years will also produce millions of low-skill service jobs resistant to automation, particularly ones that require physical dexterity in non-rote unpredictable environments. The large health care, social services, and education industries are good examples. The good news is such jobs will continue to exist and provide livelihoods. The bad news is these jobs are likely to remain difficult, unstable, and low paying. Consequently, policymakers are going to need to adopt income-support measures to improve workers’ well-being.

Today, the Earned Income Tax Credit (EITC) looks like an essentialcounterbalance to the likely continued wage stagnation and insecurity ahead for many lower-skill workers in the AI era. The program provides families with children that make under $50,000 a refundable tax credit of up to $6,300 that filers get to keep, minus any tax owed, even if it reduces their tax liability below zero. In effect, it provides a significant income subsidy for lower-wage American workers with children. What is more, the EITC is effective: it lifts nearly 6 million people per year out of poverty, and reduces the severity of poverty for nearly 19 million more, all while promoting work.[[128]](#endnote-128)

Which is why policymakers should **expand the EITC on the federal and state levels** to significantly improve its ability to support low-wage workers. First, policymakers should provide more EITC support to childless workers. While workers without children are eligible, they receive a significantly smaller subsidy that phases out at a much lower level of income. However, many workers displaced by automation will not have children—for example, they may be older workers who no longer claim their children as dependents on their taxes. Additional reforms should include raising the maximum income threshold to allow more workers to qualify for the credit and providing workers with EITC payments more regularly.[[129]](#endnote-129) The latter would serve to not only reduce poverty, but also counter the negative impacts of income volatility. Currently, the EITC is paid as one lump sum with a worker’s tax return. However, making payments on a quarterly or monthly basis would provide workers with a more predictable regular income.[[130]](#endnote-130) Finally, some 23 states plus the District of Columbia already offer a refundable state-level EITC, and another six offer non-refundable EITCs. All states that collect income taxes should implement or expand state-level EITCs.

Yet, even with a robust worker adjustment system, older displaced workers face steep costs of having to switch industries—they lose seniority and must develop an entirely new set of skills at the end of their career. Furthermore, income loss typically becomes more dramatic the longer a worker is out of the labor force, a problem that is particularly serious if adjustment happens slowly after automation-based displacement. As a result, about half of displaced workers who are rehired full-time make less than they did in their previous job, and more than 25 percent lose a fifth of their income or more.[[131]](#endnote-131) To combat this, policymakers should **create a universal wage insurance program for displaced workers**. Wage insurance programs cover a portion of the displaced worker’s lost wages if they accept a new lower paying position and can, in conjunction with policies like the EITC, alleviate some of the financial loss that workers face. Wage insurance may also encourage workers to accept a job offer sooner, even if it is lower paying, mitigating some of the negative impacts of a slow adjustment process. Currently TAA has the only wage insurance program in the U.S. It pays trade-displaced workers 55 and older who make under $50,000 per year half of the difference in lost wages, up to a maximum of $10,000, for two years.[[132]](#endnote-132)

Finally, states can support automation-impacted workers by taking steps to **expand partial unemployment benefits** for involuntary part-time workers. In recent years the number of part-time workers working involuntarily has remained elevated, a problem likely to be exacerbated by automation.[[133]](#endnote-133) While all states currently provide some level of partial unemployment benefits, they vary widely. States should follow the lead of Connecticut, Idaho, and several other states by providing partial benefits for workers making up to 150 percent of the maximum state UI benefit amount.[[134]](#endnote-134) This will not only improve part-time workers’ financial security but also allow unemployed workers to make more through part-time work than through UI payments alone, incentivizing them to return to the labor force.

**Reduce financial insecurity for workers in low-wage jobs**

The next phase of automation could well ensure that more workers wind up stuck in jobs that are not only low paying but also shaky given the nature of many of the most durable low-end service jobs. Frequently these positions lack access to basic benefits such as retirement contributions, health insurance, or paid leave. Likewise, millions of workers will continue to find themselves exposed to the insecurity associated with volatile pay, given the reality of profit-maximizing digital scheduling platforms, seasonal demand, or other factors. All of which argues for a stronger, more portable safety net as the AI era progresses.[[135]](#endnote-135) Several initiatives are critical.

For one thing, states should **enact state-run automatic individual retirement account programs** to help the 30 to 35 percent of workers in the U.S. who lack an employer-sponsored retirement plan. [[136]](#endnote-136) Auto IRA programs are an effective, non-partisan solution for expanding retirement support. In states with auto IRA laws or regulations, employers that do not provide their workers with employer-sponsored retirement plans must enroll them in a state-sponsored individual retirement account (IRA). While workers are automatically enrolled, they may opt-out at any time. However, because the accounts are structured as IRAs, most workers likely want to keep them when they move to a new job, allowing workers to save steadily even while navigating the likely instability of much AI-era employment.

**OregonSaves: The first-in-the-nation automatic IRA**

In 2016, the Obama administration gave states and localities leeway to establish voluntary automatic individual retirement accounts. However, in 2017, Congress, with support from the Trump administration, revoked this federal support, a move that was difficult to justify on any sound policy grounds.[[137]](#endnote-137) Nonetheless, despite lack of federal support, several states are pioneering efforts to create automatic IRAs.

In 2017, Oregon launched the first of these plans, known as OregonSaves. By 2020, all employers in the state that do not offer their own retirement plan will need to enroll employees in an OregonSaves IRA. To date, nearly 43,000 workers across 1,275 employers have enrolled in retirement savings plans.[[138]](#endnote-138) Program assessments have shown an employee takeup rate of over 70 percent at employers who are already participating, indicating strong demand but also flexibility for workers who do not want to participate.[[139]](#endnote-139) Furthermore, surveys conducted by the AARP indicate that over 80 percent of Oregonians support the program on a bipartisan basis.[[140]](#endnote-140)

Despite the lack of federal support, other states and municipalities are moving forward with their own state-run automatic IRAs. This includes California, which would be the largest state-run automatic IRA program in the country.

Improved health programs are also going to be essential to mitigate worker insecurity in the near future. And here the needed actions are pretty clear. Federal, state, and city policymakers should **enact paid sick and family leave for all workers** since so many workers, particularly in the service industry, do not get those protections. In fact, in 2017 nearly 30 percent of U.S. workers lacked access to paid sick leave and 85 percent lacked paid family leave.[[141]](#endnote-141) Likewise, state leaders should **expand Medicaid in the 18 states that have not yet done so**. And on the federal level, Congress and the executive branch should **end efforts to sabotage ACA coverage gains**. Finally, policymakers on the federal, state, and local levels should **create public health care options** for both group and individual insurance coverage. As automation continues to create new types of work, individuals will need to embrace adaptability and an entrepreneurial spirit. Universal health benefits would allow workers to take necessary risks without having to fear for their health or the health of their families.

As automation and AI continue to displace workers, meanwhile, more workers may need to rely on nonstandard work. While the exact number is debated, it is clear that millions of low-income workers work in the “contingent economy,” a broad group of workers including temporary workers, independent contractors and subcontractors, “gig economy,” and internet-based platform workers, and on-call workers, among others.[[142]](#endnote-142) Others work as part-time employees for multiple companies, particularly in service industries such as retail and foodservice. Many of these workers are paid by multiple stakeholders, and few receive worker benefits.

One model to support these workers is to **introduce portable benefits programs** on the state or local level. Portable benefits can help workers with multiple employers access the same supports as traditional wage workers, regardless of who they are working for and on what terms. The Aspen Institute defines portable benefits as having three key characteristics:[[143]](#endnote-143)

* Workers own their benefits (i.e. they are not tied to a specific job or company).
* Companies make contributions at a fixed rate based on how much a worker works for them.
* The benefits cover independent workers, not just traditional employees.

State governments in Washington, California, New York, and New Jersey are all exploring how best to implement a portable benefits system, with Washington the furthest along. More states should take steps to create programs, and the federal government should support these efforts by passing previously proposed legislation to provide financial assistance to states pioneering portable benefits.

For other workers, the rise of new technologies such as just-in-time scheduling software have increased firm efficiency at the expense of staff work hours. Workers in low-wage, high-growth service industries often have minimal input into their schedules, which can change with little-to-no advance notice. In other cases, workers are required to be on-call for shifts, and may not know whether they are working until they arrive. [[144]](#endnote-144) This has led to paycheck uncertainty for a significant portion of American workers, with individuals facing wide swings in their monthly income.[[145]](#endnote-145) One of the most effective ways for states and localities to mitigate paycheck volatility and improve workers’ quality of life is to **implement fair scheduling policies**. Fair scheduling policies mitigate the impacts by requiring firms to take actions such as creating schedules as least two weeks in advance and providing additional pay for last-minute schedule changes or on-call shifts. These policies aren’t just good for workers—they can also have positive impacts for corporate bottom lines. For example, a 2018 study by the University of California, University of Chicago, and University of North Carolina found that retail stores that implemented stable scheduling policies saw both an increase in worker productivity and greater sales.[[146]](#endnote-146)

The general point is unavoidable. With digital technologies likely to roil the wage continuum and increase near- and medium-term hardship for low-wage workers, society needs to do more to improve the lot of those who for whatever reason cannot secure a more comfortable position in the AI economy.

**Mitigate harsh local impacts**

Working to alleviate individuals’ automation-related hardships alone won’t be sufficient, however. Individuals’ work lives are inextricably shaped by their local labor markets, and the extent of automation-related disruption varies significantly by place. For that reason, any comprehensive adjustment strategy for the AI era needs also to address the resilience of hard-hit communities.

Fortunately, precedents for action exist. The federal government, in conjunction with state and local entities, provides support for a variety of place-oriented and regional economic development programs. The Economic Development Agency (EDA) operates several adjustment programs, such as the Economic Adjustment Assistance Program and Trade Adjustment Assistance for Firms, aimed at helping distressed communities adapt to changing economic realities.[[147]](#endnote-147) Other agencies such as the Appalachian Regional Commission (ARC) and Delta Regional Authority (DRA) focus on supporting workforce, business development, and infrastructure investment in specific distressed areas.[[148]](#endnote-148) Still others, such as the various industry cluster and innovation challenge grants run by the EDA and the Small Business Administration (SBA) focus on regionally designed initiatives for advancing local clusters.[[149]](#endnote-149) Such programs have had, and can play, a useful role in helping communities adjust to disruptions.[[150]](#endnote-150)

Yet, these programs remain underfunded and diffuse and operate largely independent of other workforce development and retraining programs, such as the Workforce Innovation and Opportunity Act (WIOA). The result: Economic development investments in troubled areas aren’t always aligned with broader efforts to local areas’ fortunes.[[151]](#endnote-151) Ultimately, none of these programs are specifically oriented to addressing the kind of worker and community dislocation that may accompany wider adoption of AI.

In view of that, federal and state policymakers need to improve the effectiveness of their efforts to help distressed communities adjust to disruptive trends.[[152]](#endnote-152) The need for tech-related community adjustment mirrors the long-recognized need to respond to local trade or military-related dislocations with programs such as TAA and Defense Adjustment.[[153]](#endnote-153) Likewise, such intervention parallels broader concerns about helping a wider array of “places left behind,” many of which have been negatively impacted by the rise of robots and other forms of labor automation at a moment of political and cultural division.[[154]](#endnote-154)

What should such efforts look like? Two strategies for response appear essential:

* Future-proof vulnerable regional economies
* Expand support for community adjustment

**Future-proof vulnerable regional economies**

A first need is to equip places hurt by technology change to become more resilient. Such efforts must begin with a focus on future-proofing workers in these places by striving to **impart skills that lead to automation-resilient work**.

Here regional and state-led initiatives show promise. For example, the SkillUp program in Northeast Ohio’s Cuyahoga County leverages local firms to facilitate regional skill development for in-demand jobs. The program helps firms in the region identify future workforce needs through a strategic planning process, determines the skills required for those jobs, and develops customized roadmaps to evaluate workers’ existing skills and facilitate training for in-demand positions. Training focuses on three types of skills: soft skills, foundational skills, and technical/occupational skills, which, when combined, make workers more adaptable to the labor market impacts of automation.[[155]](#endnote-155) Empirical studies show that such employer-specific training programs are an effective way to increase worker productivity, employment, and earnings.[[156]](#endnote-156)

Likewise, the Skillful initiative’s State Network and Playbook indicates the steps regions must take to reorient their workforce toward in-demand skills. Beyond just workforce planning, firms must shift hiring processes, educators and trainers must change how they teach, and policymakers must enhance career navigation for jobseekers—all with a focus on prioritizing skill development and recognition in an increasingly digital economy.[[157]](#endnote-157) Such efforts will grow in importance as automation and AI increase the pace of task change and ordain that workers either master new ways of either working with the machines, or working beyond them.

For its part, the federal government should reorient its funding streams to support such efforts. This includes supporting bottom-up local solutions and incentivizing regions to align their education, workforce and training, and economic development systems with one another as well as with employers’ specific needs and with the new importance of higher-order soft skills. The goal should be to create clear pipelines of skills acquisition aimed squarely at ensuring that regional economies becomes sources of resilient workers skilled in bringing value in an era when the machines do the rote stuff. The federal government can also work to coordinate efforts among different regions, and to support the development of centers of excellence or growth poles throughout the country.

Relatedly, governments should seek to **accelerate the adoption of intelligent technology by regional economies** and firms likely to be left behind as a parallel effort to help places become more resilient. This should begin with both the federal and state governments ramping up their extension missions by investing more in efforts to broaden the application, adoption, and commercialization of automation and AI innovations—including through organizational transformation. On this front, the successful Manufacturing Extension Partnership (MEP) network offers a 50-state, 30-year precedent for equipping small- and medium-sized manufacturing with higher-tech productivity solutions, including in rural places.[[158]](#endnote-158) Building on that history, the United States. now needs a broader, bolder MEP-style program designed to diffuse high-tech and AI applications and organizational transformations into all corners of the economy, including the service sector.

Growth in these regions will only be sustainable, however, if the U.S. maintains a robust pipeline of AI-related research and commercialization. Policymakers therefore must **expand government research** in crucial AI- and automation-related areas, such as digitalization and robotics. More specifically, further experimentation with the use of region- and sector-based applied research centers would benefit both places themselves and broader government research efforts. This promising model is exemplified by the federal government’s network of Manufacturing USA institutes, including the Advanced Robotics for Manufacturing (ARM) center in Pittsburgh and the Digital Manufacturing and Design Innovation Institute (DMDII) in Chicago.[[159]](#endnote-159) Localized, theme-based nodes within a larger network of distributed research centers are demonstrating a powerful way of spurring R&D innovation and commercialization.[[160]](#endnote-160) The ARM and DMDII institutes each also include among their missions the demonstration and diffusion of digital and automation technologies, including to small-and-medium-sized enterprises (SMEs), which further enhances the government’s “extension” mission. The model has great potential for delivering further work on automation.

**Expand support for community adjustment**

And yet, not even successful efforts to promote more communities’ resilience will prevent substantial harm to others. As this report has shown, the spatial impacts of automation will not be spread evenly. Some regions, in particular those on the smaller end of the size distribution, are going to suffer much more disruption than others. For that reason, federal and state policymakers need to complement efforts to boost local resilience with special targeted interventions to mitigate the worst local impacts of automation. Here there are antecedents as well, such as the EDA’s Adjustment Program, or the Department of Energy’s Partnerships for Opportunity and Workforce and Economic Revitalization (POWER) program, aimed at communities impacted by changes in energy policy.[[161]](#endnote-161) However, these programs’ modest scale and disjointed coordination limits their impact. In order to improve effectiveness, a more robust national strategy may well be needed.

Such an initiative would likely begin by marshaling government and private sector resources into affected communities, and should be complemented with efforts to boost labor demand in those areas. Governments should first leverage public and private sector resources to **channel job-creating investment into communities and places being adversely affected** by automation, recognizing that some places are experiencing more displacement than others.[[162]](#endnote-162) Placing federal or state assets in such places—in conjunction with efforts to spark entrepreneurship by streamlining regulations—could help.[[163]](#endnote-163) So could explicit regional catch-up programs.[[164]](#endnote-164)

With that said, the history of U.S. strategy to spur growth and development in communities and regions has been to give small ad hoc grants to many places, few of which have prospects for a turnaround without sustained intensive investment. A more effective strategy would be to give extensive support to a few areas, with the goal of producing hubs for regional growth. In this regard, the federal government should offer support to 10 or so medium-sized metro areas, to be selected through a competitive grant process, to serve as regional growth poles. This investment would consist of a suite of research, tax, infrastructure, and economic development benefits from the government, and would be coupled with corresponding investment by states and the private sector. Through this, growth poles would serve as anchors to enhance growth in the larger surrounding regions.[[165]](#endnote-165)

**Defense adjustment programs**

The Department of Defense (DOD) is the U.S. government’s largest department in spending, personnel, and physical infrastructure. As a result, changes to its programs and force structure can have significant economic impacts. For communities, the closure of a military base or cancellation of a DOD program has an impact similar to the closure of a factory or business due to automation, and can cause major disruptions for contractors and manufacturers throughout the supply chain.

In response, the DOD Office of Economic Adjustment (OEA) helps communities adapt to base closures through its BRAC assistance program, and to DOD program cancellations through its Defense Industry Adjustment program. These programs provide a variety of different supports for communities and firms. Most importantly, they provide grants and project management to help eligible communities develop adjustment plans. Additional resources include funding to develop plans to reuse military facilities, support in securing other federal funding and resources, and helping to facilitate the exchange of best practices among communities.[[166]](#endnote-166)

According to a 2013 report by the Government Accountability Office, communities impacted by base closures see OEA as an asset. Furthermore, the GAO report found that, despite the significant dislocations caused by the base closures, slight majorities of BRAC-impacted communities had unemployment rates at or below the national average, and growth rates above the national average.[[167]](#endnote-167)

Similarly, the widely-discussed Opportunity Zones program created by the Tax Cuts and Jobs Act of 2017 may help some states and investors **target investment to boost labor demand** in struggling places. As with other place-sensitive efforts, targeted investments should be coupled with shrewdly attuned training modules. For example, states should encourage companies opening new facilities in Opportunity Zones to develop specialized training programs tailored to their emerging labor needs and to hire program graduates.

Beyond that, it is likely that stronger tools—such as spatially targeted hiring credits, job subsidies, or job guarantees—will be needed in many of the communities that will be hardest hit by task change. Such supports—focused on new hires (so as not to provide windfall benefits on existing jobs)—would be aimed at areas experiencing particularly painful or slow adjustment, and they would naturally incentivize investment to go with the jobs. Economists as diverse as Ed Glaeser, Larry Summers, Robert Litan, and David Neumark have all affirmed the need for such strong pro-work interventions in certain struggling places where automation has sapped labor demand.[[168]](#endnote-168)

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As this paper as shown, while AI and automation will have many positive impacts on the U.S. economy, they have nonetheless led to significant labor market disruptions and are likely to continue doing so. To date, the lack of comprehensive adjustment strategy has exacerbated the impacts of automation on the U.S. workforce. However, past does not need to be prologue. Through a deliberate, coordinated adjustment effort on the federal, state, and local levels, policymakers, business leaders, and civil society can enhance growth, mitigate the most negative labor market impacts of automation, and sustain U.S. competitiveness in an increasingly AI-driven global economy.

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Appendix A. Occupations’ automation potential

|  |  |  |
| --- | --- | --- |
| **Rank** | **Occupation** | **Automation potential** |
| 1 | Machine Feeders and Offbearers | 100% |
| 2 | Dredge Operators | 100% |
| 3 | Aircraft Cargo Handling Supervisors | 100% |
| 4 | Packaging and Filling Machine Operators and Tenders | 100% |
| 5 | Ophthalmic Laboratory Technicians | 100% |
| 6 | Medical Appliance Technicians | 100% |
| 7 | Foundry Mold and Coremakers | 100% |
| 8 | Slaughterers and Meat Packers | 100% |
| 9 | Plasterers and Stucco Masons | 100% |
| 10 | Logging Equipment Operators | 100% |
| 11 | Graders and Sorters, Agricultural Products | 100% |
| 12 | Motion Picture Projectionists | 100% |
| 13 | Bridge and Lock Tenders | 99.9% |
| 14 | Medical Equipment Preparers | 99.5% |
| 15 | Mine Cutting and Channeling Machine Operators | 99.4% |
| 16 | Paper Goods Machine Setters, Operators, and Tenders | 98.9% |
| 17 | Pressers, Textile, Garment, and Related Materials | 98.7% |
| 18 | Cooling and Freezing Equipment Operators and Tenders | 98.3% |
| 19 | Sewing Machine Operators | 97.9% |
| 20 | Production Workers, All Other | 97.2% |
| 21 | Dental Laboratory Technicians | 97.1% |
| 22 | Coating, Painting, and Spraying Machine Setters, Operators, and Tenders | 97.0% |
| 23 | Helpers--Production Workers | 97.0% |
| 24 | Cutters and Trimmers, Hand | 96.7% |
| 25 | Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers | 96.6% |
| 26 | Tailors, Dressmakers, and Custom Sewers | 96.4% |
| 27 | Continuous Mining Machine Operators | 96.1% |
| 28 | Meat, Poultry, and Fish Cutters and Trimmers | 96.0% |
| 29 | Metal-Refining Furnace Operators and Tenders | 95.8% |
| 30 | Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders | 95.4% |
| 31 | Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic | 95.3% |
| 32 | Terrazzo Workers and Finishers | 95.0% |
| 33 | Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic | 94.9% |
| 34 | Photographic Process Workers and Processing Machine Operators | 94.7% |
| 35 | Food Processing Workers, All Other | 94.6% |
| 36 | Computer-Controlled Machine Tool Operators, Metal and Plastic | 94.6% |
| 37 | Subway and Streetcar Operators | 94.5% |
| 38 | Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic | 94.1% |
| 39 | Gas Compressor and Gas Pumping Station Operators | 93.9% |
| 40 | Mail Clerks and Mail Machine Operators, Except Postal Service | 93.7% |
| 41 | Plant and System Operators, All Other | 93.6% |
| 42 | Bakers | 93.5% |
| 43 | Prepress Technicians and Workers | 93.4% |
| 44 | Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic | 93.3% |
| 45 | Sawing Machine Setters, Operators, and Tenders, Wood | 93.1% |
| 46 | Radio Operators | 93.1% |
| 47 | Sewers, Hand | 93.0% |
| 48 | Food Batchmakers | 92.9% |
| 49 | Office Machine Operators, Except Computer | 92.9% |
| 50 | Butchers and Meat Cutters | 92.8% |
| 51 | Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic | 92.7% |
| 52 | Earth Drillers, Except Oil and Gas | 92.7% |
| 53 | Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic | 92.5% |
| 54 | Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders | 92.4% |
| 55 | Floor Layers, Except Carpet, Wood, and Hard Tiles | 92.3% |
| 56 | Mixing and Blending Machine Setters, Operators, and Tenders | 92.3% |
| 57 | Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders | 92.2% |
| 58 | Tire Repairers and Changers | 92.1% |
| 59 | Welders, Cutters, Solderers, and Brazers | 91.9% |
| 60 | Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders | 91.8% |
| 61 | Structural Metal Fabricators and Fitters | 91.7% |
| 62 | Food Cooking Machine Operators and Tenders | 91.7% |
| 63 | Industrial Truck and Tractor Operators | 91.7% |
| 64 | Wellhead Pumpers | 91.7% |
| 65 | Woodworking Machine Setters, Operators, and Tenders, Except Sawing | 91.4% |
| 66 | Food Preparation Workers | 91.4% |
| 67 | Cooks, Short Order | 91.2% |
| 68 | Cutting and Slicing Machine Setters, Operators, and Tenders | 91.2% |
| 69 | Painters, Transportation Equipment | 91.2% |
| 70 | Grinding and Polishing Workers, Hand | 90.6% |
| 71 | Word Processors and Typists | 90.4% |
| 72 | Furniture Finishers | 90.3% |
| 73 | Carpet Installers | 90.2% |
| 74 | Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic | 90.2% |
| 75 | Cooks, Institution and Cafeteria | 90.0% |
| 76 | Painters, Construction and Maintenance | 89.8% |
| 77 | Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic | 89.7% |
| 78 | Sound Engineering Technicians | 89.6% |
| 79 | Phlebotomists | 89.4% |
| 80 | Upholsterers | 89.3% |
| 81 | Shoe Machine Operators and Tenders | 89.2% |
| 82 | Laundry and Dry-Cleaning Workers | 89.1% |
| 83 | Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders | 89.1% |
| 84 | Sailors and Marine Oilers | 89.0% |
| 85 | Traffic Technicians | 88.8% |
| 86 | Power Plant Operators | 88.7% |
| 87 | Chemical Equipment Operators and Tenders | 88.7% |
| 88 | Fiberglass Laminators and Fabricators | 88.7% |
| 89 | Rolling Machine Setters, Operators, and Tenders, Metal and Plastic | 88.6% |
| 90 | Cooks, Fast Food | 88.5% |
| 91 | Textile, Apparel, and Furnishings Workers, All Other | 88.5% |
| 92 | Cement Masons and Concrete Finishers | 88.3% |
| 93 | Operating Engineers and Other Construction Equipment Operators | 88.2% |
| 94 | Counter Attendants, Cafeteria, Food Concession, and Coffee Shop | 88.1% |
| 95 | Jewelers and Precious Stone and Metal Workers | 88.1% |
| 96 | Automotive Glass Installers and Repairers | 88.0% |
| 97 | Molders, Shapers, and Casters, Except Metal and Plastic | 87.8% |
| 98 | Billing and Posting Clerks | 87.6% |
| 99 | Tool Grinders, Filers, and Sharpeners | 87.5% |
| 100 | Conveyor Operators and Tenders | 87.4% |
| 101 | Metal Workers and Plastic Workers, All Other | 87.4% |
| 102 | Payroll and Timekeeping Clerks | 87.4% |
| 103 | Print Binding and Finishing Workers | 87.1% |
| 104 | Cooks, All Other | 87.1% |
| 105 | Tile and Marble Setters | 87.0% |
| 106 | Tool and Die Makers | 86.9% |
| 107 | Combined Food Preparation and Serving Workers, Including Fast Food | 86.7% |
| 108 | Textile Bleaching and Dyeing Machine Operators and Tenders | 86.7% |
| 109 | Stock Clerks and Order Fillers | 86.4% |
| 110 | Data Entry Keyers | 86.4% |
| 111 | Textile Cutting Machine Setters, Operators, and Tenders | 86.4% |
| 112 | Forging Machine Setters, Operators, and Tenders, Metal and Plastic | 86.3% |
| 113 | Dining Room and Cafeteria Attendants and Bartender Helpers | 86.2% |
| 114 | Printing Press Operators | 86.1% |
| 115 | Loading Machine Operators, Underground Mining | 86.1% |
| 116 | Pourers and Casters, Metal | 86.0% |
| 117 | Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders | 85.8% |
| 118 | Dishwashers | 85.6% |
| 119 | Bookkeeping, Accounting, and Auditing Clerks | 85.6% |
| 120 | Paving, Surfacing, and Tamping Equipment Operators | 85.6% |
| 121 | Automotive Body and Related Repairers | 85.4% |
| 122 | Bus Drivers, Transit and Intercity | 85.4% |
| 123 | Adhesive Bonding Machine Operators and Tenders | 85.2% |
| 124 | Chemical Plant and System Operators | 85.1% |
| 125 | Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic | 85.0% |
| 126 | Fabric Menders, Except Garment | 84.8% |
| 127 | Paperhangers | 84.7% |
| 128 | Crane and Tower Operators | 84.5% |
| 129 | Parts Salespersons | 84.5% |
| 130 | Craft Artists | 84.5% |
| 131 | Agricultural Equipment Operators | 84.1% |
| 132 | Cooks, Restaurant | 84.0% |
| 133 | Rotary Drill Operators, Oil and Gas | 83.8% |
| 134 | Woodworkers, All Other | 83.5% |
| 135 | Etchers and Engravers | 83.4% |
| 136 | Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders | 83.4% |
| 137 | Stationary Engineers and Boiler Operators | 83.1% |
| 138 | Shoe and Leather Workers and Repairers | 83.0% |
| 139 | Mining Machine Operators, All Other | 82.2% |
| 140 | Excavating and Loading Machine and Dragline Operators | 82.1% |
| 141 | Motor Vehicle Operators, All Other | 81.7% |
| 142 | Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic | 81.5% |
| 143 | Heavy and Tractor-Trailer Truck Drivers | 81.4% |
| 144 | Driver/Sales Workers | 81.4% |
| 145 | Coil Winders, Tapers, and Finishers | 81.1% |
| 146 | Petroleum Pump System Operators, Refinery Operators, and Gaugers | 81.1% |
| 147 | Electronic Equipment Installers and Repairers, Motor Vehicles | 80.8% |
| 148 | Patternmakers, Wood | 80.6% |
| 149 | Insurance Claims and Policy Processing Clerks | 80.6% |
| 150 | Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders | 80.5% |
| 151 | Tapers | 80.2% |
| 152 | Library Assistants, Clerical | 80.1% |
| 153 | Postal Service Mail Sorters, Processors, and Processing Machine Operators | 80.1% |
| 154 | Segmental Pavers | 80.0% |
| 155 | Food Preparation and Serving Related Workers, All Other | 79.9% |
| 156 | Bus and Truck Mechanics and Diesel Engine Specialists | 79.9% |
| 157 | Bicycle Repairers | 79.8% |
| 158 | Textile Knitting and Weaving Machine Setters, Operators, and Tenders | 79.8% |
| 159 | Transportation Attendants, Except Flight Attendants | 79.6% |
| 160 | Machinists | 79.6% |
| 161 | Packers and Packagers, Hand | 79.5% |
| 162 | Rock Splitters, Quarry | 79.3% |
| 163 | Gas Plant Operators | 79.0% |
| 164 | Patternmakers, Metal and Plastic | 78.9% |
| 165 | File Clerks | 78.7% |
| 166 | Model Makers, Metal and Plastic | 78.7% |
| 167 | Shipping, Receiving, and Traffic Clerks | 78.6% |
| 168 | Correspondence Clerks | 78.5% |
| 169 | Light Truck or Delivery Services Drivers | 78.2% |
| 170 | Tellers | 78.1% |
| 171 | Legal Secretaries | 77.9% |
| 172 | Bus Drivers, School or Special Client | 77.7% |
| 173 | Aircraft Mechanics and Service Technicians | 77.2% |
| 174 | Waiters and Waitresses | 76.9% |
| 175 | Nuclear Technicians | 76.9% |
| 176 | Millwrights | 76.6% |
| 177 | Outdoor Power Equipment and Other Small Engine Mechanics | 76.6% |
| 178 | Captains, Mates, and Pilots of Water Vessels | 76.5% |
| 179 | Taxi Drivers and Chauffeurs | 76.0% |
| 180 | Flight Attendants | 75.3% |
| 181 | Railroad Brake, Signal, and Switch Operators | 75.2% |
| 182 | Floor Sanders and Finishers | 75.1% |
| 183 | Nuclear Power Reactor Operators | 74.6% |
| 184 | Precision Instrument and Equipment Repairers, All Other | 74.3% |
| 185 | Transportation Security Screeners | 74.2% |
| 186 | Stonemasons | 74.1% |
| 187 | Electromechanical Equipment Assemblers | 74.0% |
| 188 | Log Graders and Scalers | 73.8% |
| 189 | Manicurists and Pedicurists | 73.8% |
| 190 | Hairdressers, Hairstylists, and Cosmetologists | 73.7% |
| 191 | Rail Car Repairers | 73.7% |
| 192 | Derrick Operators, Oil and Gas | 73.6% |
| 193 | Model Makers, Wood | 73.4% |
| 194 | Automotive Service Technicians and Mechanics | 73.4% |
| 195 | Barbers | 73.3% |
| 196 | Motorboat Operators | 73.3% |
| 197 | Travel Agents | 73.1% |
| 198 | Power Distributors and Dispatchers | 73.0% |
| 199 | Motorboat Mechanics and Service Technicians | 72.8% |
| 200 | Medical Transcriptionists | 72.8% |
| 201 | Timing Device Assemblers and Adjusters | 72.7% |
| 202 | Assemblers and Fabricators, All Other | 72.7% |
| 203 | Slot Supervisors | 72.6% |
| 204 | Service Unit Operators, Oil, Gas, and Mining | 72.6% |
| 205 | Loan Interviewers and Clerks | 72.6% |
| 206 | Postal Service Mail Carriers | 72.5% |
| 207 | Financial Clerks, All Other | 72.5% |
| 208 | Office and Administrative Support Workers, All Other | 72.5% |
| 209 | Airline Pilots, Copilots, and Flight Engineers | 72.4% |
| 210 | Cabinetmakers and Bench Carpenters | 72.3% |
| 211 | Pump Operators, Except Wellhead Pumpers | 72.1% |
| 212 | Computer User Support Specialists | 71.9% |
| 213 | Medical Equipment Repairers | 71.8% |
| 214 | Telephone Operators | 71.7% |
| 215 | Parking Lot Attendants | 71.5% |
| 216 | Electrical and Electronics Repairers, Powerhouse, Substation, and Relay | 71.2% |
| 217 | Semiconductor Processors | 71.2% |
| 218 | Communications Equipment Operators, All Other | 71.0% |
| 219 | Weighers, Measurers, Checkers, and Samplers, Recordkeeping | 71.0% |
| 220 | Switchboard Operators, Including Answering Service | 70.3% |
| 221 | Postal Service Clerks | 70.3% |
| 222 | Pharmacy Technicians | 70.1% |
| 223 | Engine and Other Machine Assemblers | 70.0% |
| 224 | Skincare Specialists | 70.0% |
| 225 | Septic Tank Servicers and Sewer Pipe Cleaners | 69.6% |
| 226 | Desktop Publishers | 69.5% |
| 227 | Pesticide Handlers, Sprayers, and Applicators, Vegetation | 69.5% |
| 228 | Cargo and Freight Agents | 69.4% |
| 229 | Layout Workers, Metal and Plastic | 69.3% |
| 230 | Biological Technicians | 69.3% |
| 231 | Paralegals and Legal Assistants | 69.2% |
| 232 | Procurement Clerks | 69.1% |
| 233 | Gaming Managers | 68.6% |
| 234 | Installation, Maintenance, and Repair Workers, All Other | 68.3% |
| 235 | Farm Equipment Mechanics and Service Technicians | 68.1% |
| 236 | Automotive and Watercraft Service Attendants | 68.0% |
| 237 | Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic | 68.0% |
| 238 | Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop | 68.0% |
| 239 | Tire Builders | 67.9% |
| 240 | First-Line Supervisors of Mechanics, Installers, and Repairers | 67.7% |
| 241 | Bartenders | 67.5% |
| 242 | Watch Repairers | 67.4% |
| 243 | Rail Transportation Workers, All Other | 67.1% |
| 244 | Police, Fire, and Ambulance Dispatchers | 67.0% |
| 245 | Judicial Law Clerks | 67.0% |
| 246 | Cooks, Private Household | 66.7% |
| 247 | Brokerage Clerks | 66.7% |
| 248 | Insulation Workers, Mechanical | 65.8% |
| 249 | Concierges | 65.8% |
| 250 | Cartographers and Photogrammetrists | 65.7% |
| 251 | Information Security Analysts | 65.4% |
| 252 | Camera and Photographic Equipment Repairers | 65.2% |
| 253 | Inspectors, Testers, Sorters, Samplers, and Weighers | 64.8% |
| 254 | Geoscientists, Except Hydrologists and Geographers | 64.7% |
| 255 | Locker Room, Coatroom, and Dressing Room Attendants | 64.6% |
| 256 | Mechanical Door Repairers | 64.3% |
| 257 | Water and Wastewater Treatment Plant and System Operators | 64.2% |
| 258 | Medical and Clinical Laboratory Technicians | 64.1% |
| 259 | Fallers | 64.0% |
| 260 | Electrical and Electronic Equipment Assemblers | 64.0% |
| 261 | First-Line Supervisors of Food Preparation and Serving Workers | 63.8% |
| 262 | Shampooers | 63.5% |
| 263 | Network and Computer Systems Administrators | 63.5% |
| 264 | Computer Operators | 63.4% |
| 265 | Costume Attendants | 63.2% |
| 266 | Logging Workers, All Other | 62.6% |
| 267 | Food Servers, Nonrestaurant | 62.2% |
| 268 | Electronic Home Entertainment Equipment Installers and Repairers | 62.2% |
| 269 | Broadcast Technicians | 62.0% |
| 270 | Pharmacy Aides | 61.9% |
| 271 | Explosives Workers, Ordnance Handling Experts, and Blasters | 61.8% |
| 272 | Computer Network Support Specialists | 61.7% |
| 273 | Aerospace Engineering and Operations Technicians | 61.6% |
| 274 | Occupational Health and Safety Technicians | 61.6% |
| 275 | Office Clerks, General | 61.5% |
| 276 | Wind Turbine Service Technicians | 61.2% |
| 277 | Surveying and Mapping Technicians | 60.8% |
| 278 | Fabric and Apparel Patternmakers | 60.5% |
| 279 | Statistical Assistants | 60.4% |
| 280 | Hazardous Materials Removal Workers | 60.3% |
| 281 | Insurance Sales Agents | 60.2% |
| 282 | Motorcycle Mechanics | 60.0% |
| 283 | Entertainment Attendants and Related Workers, All Other | 59.8% |
| 284 | Gaming Service Workers, All Other | 59.8% |
| 285 | Physical Scientists, All Other | 59.8% |
| 286 | Aircraft Structure, Surfaces, Rigging, and Systems Assemblers | 59.7% |
| 287 | Avionics Technicians | 59.7% |
| 288 | First-Line Supervisors of Housekeeping and Janitorial Workers | 59.7% |
| 289 | Museum Technicians and Conservators | 59.5% |
| 290 | Library Technicians | 59.1% |
| 291 | Recreational Vehicle Service Technicians | 59.0% |
| 292 | Amusement and Recreation Attendants | 59.0% |
| 293 | Meter Readers, Utilities | 58.8% |
| 294 | Hotel, Motel, and Resort Desk Clerks | 58.7% |
| 295 | Executive Secretaries and Executive Administrative Assistants | 58.6% |
| 296 | Life, Physical, and Social Science Technicians, All Other | 58.4% |
| 297 | Grounds Maintenance Workers, All Other | 58.3% |
| 298 | Protective Service Workers, All Other | 58.3% |
| 299 | Locomotive Firers | 58.2% |
| 300 | Commercial Pilots | 58.2% |
| 301 | Credit Authorizers, Checkers, and Clerks | 58.0% |
| 302 | Counter and Rental Clerks | 57.6% |
| 303 | Medical Secretaries | 57.5% |
| 304 | Order Clerks | 57.2% |
| 305 | Ushers, Lobby Attendants, and Ticket Takers | 56.7% |
| 306 | Information and Record Clerks, All Other | 56.3% |
| 307 | Forest Fire Inspectors and Prevention Specialists | 56.1% |
| 308 | Air Traffic Controllers | 56.1% |
| 309 | Hearing Aid Specialists | 55.8% |
| 310 | Surveyors | 55.6% |
| 311 | Radio, Cellular, and Tower Equipment Installers and Repairers | 54.4% |
| 312 | Medical Assistants | 54.4% |
| 313 | Gaming Surveillance Officers and Gaming Investigators | 54.3% |
| 314 | Title Examiners, Abstractors, and Searchers | 54.2% |
| 315 | Gaming Cage Workers | 54.2% |
| 316 | Court, Municipal, and License Clerks | 54.1% |
| 317 | Insulation Workers, Floor, Ceiling, and Wall | 54.1% |
| 318 | Electrical and Electronics Installers and Repairers, Transportation Equipment | 54.1% |
| 319 | Rail Yard Engineers, Dinkey Operators, and Hostlers | 54.0% |
| 320 | Chefs and Head Cooks | 53.7% |
| 321 | Secretaries and Administrative Assistants, Except Legal, Medical, and Executive | 53.6% |
| 322 | Chemical Technicians | 53.3% |
| 323 | Health Technologists and Technicians, All Other | 52.9% |
| 324 | Veterinary Technologists and Technicians | 52.7% |
| 325 | Receptionists and Information Clerks | 52.6% |
| 326 | Brickmasons and Blockmasons | 52.6% |
| 327 | Media and Communication Equipment Workers, All Other | 52.1% |
| 328 | Surgical Technologists | 52.1% |
| 329 | Team Assemblers | 51.9% |
| 330 | Computer Network Architects | 51.5% |
| 331 | Floral Designers | 51.4% |
| 332 | Real Estate Brokers | 51.2% |
| 333 | Rail-Track Laying and Maintenance Equipment Operators | 51.1% |
| 334 | Dental Assistants | 51.0% |
| 335 | New Accounts Clerks | 50.7% |
| 336 | Human Resources Assistants, Except Payroll and Timekeeping | 50.5% |
| 337 | Locomotive Engineers | 50.5% |
| 338 | Mine Shuttle Car Operators | 50.5% |
| 339 | Plumbers, Pipefitters, and Steamfitters | 50.3% |
| 340 | Musical Instrument Repairers and Tuners | 50.3% |
| 341 | Carpenters | 50.3% |
| 342 | Gaming Change Persons and Booth Cashiers | 50.2% |
| 343 | Parking Enforcement Workers | 49.7% |
| 344 | Geological and Petroleum Technicians | 49.5% |
| 345 | Medical Records and Health Information Technicians | 49.4% |
| 346 | Ophthalmic Medical Technicians | 49.3% |
| 347 | Telemarketers | 49.1% |
| 348 | Production, Planning, and Expediting Clerks | 48.9% |
| 349 | Tax Preparers | 48.9% |
| 350 | Farmworkers and Laborers, Crop, Nursery, and Greenhouse | 48.7% |
| 351 | Cashiers | 48.6% |
| 352 | Bailiffs | 48.1% |
| 353 | Diagnostic Medical Sonographers | 48.1% |
| 354 | Radiologic Technologists | 47.4% |
| 355 | Microbiologists | 47.4% |
| 356 | First-Line Supervisors of Police and Detectives | 47.1% |
| 357 | Pharmacists | 47.0% |
| 358 | Retail Salespersons | 46.8% |
| 359 | Helpers--Carpenters | 46.7% |
| 360 | Makeup Artists, Theatrical and Performance | 46.6% |
| 361 | Drywall and Ceiling Tile Installers | 46.5% |
| 362 | Extraction Workers, All Other | 46.5% |
| 363 | Agricultural Workers, All Other | 46.4% |
| 364 | Legal Support Workers, All Other | 46.4% |
| 365 | Refractory Materials Repairers, Except Brickmasons | 46.3% |
| 366 | Pile-Driver Operators | 46.3% |
| 367 | Control and Valve Installers and Repairers, Except Mechanical Door | 46.1% |
| 368 | Securities, Commodities, and Financial Services Sales Agents | 46.0% |
| 369 | Railroad Conductors and Yardmasters | 45.9% |
| 370 | Painting, Coating, and Decorating Workers | 45.8% |
| 371 | Boilermakers | 45.8% |
| 372 | Computer, Automated Teller, and Office Machine Repairers | 45.6% |
| 373 | Manufactured Building and Mobile Home Installers | 45.5% |
| 374 | First-Line Supervisors of Fire Fighting and Prevention Workers | 45.5% |
| 375 | Pipelayers | 45.4% |
| 376 | Electrical and Electronics Repairers, Commercial and Industrial Equipment | 45.4% |
| 377 | Bill and Account Collectors | 45.3% |
| 378 | Cardiovascular Technologists and Technicians | 45.3% |
| 379 | Tour Guides and Escorts | 45.2% |
| 380 | Medical and Clinical Laboratory Technologists | 45.1% |
| 381 | First-Line Supervisors of Personal Service Workers | 45.1% |
| 382 | Audio-Visual and Multimedia Collections Specialists | 44.9% |
| 383 | Transportation Workers, All Other | 44.8% |
| 384 | Occupational Therapy Aides | 44.6% |
| 385 | Radiation Therapists | 44.3% |
| 386 | Nursing Assistants | 44.2% |
| 387 | Dietitians and Nutritionists | 44.2% |
| 388 | First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators | 43.9% |
| 389 | First-Line Supervisors of Correctional Officers | 43.8% |
| 390 | First-Line Supervisors of Protective Service Workers, All Other | 43.6% |
| 391 | Audiologists | 43.3% |
| 392 | Ship Engineers | 43.1% |
| 393 | Librarians | 43.0% |
| 394 | Web Developers | 42.6% |
| 395 | Dietetic Technicians | 42.5% |
| 396 | Camera Operators, Television, Video, and Motion Picture | 42.5% |
| 397 | Electricians | 42.4% |
| 398 | Technical Writers | 42.3% |
| 399 | Audio and Video Equipment Technicians | 41.9% |
| 400 | Glaziers | 41.8% |
| 401 | Correctional Officers and Jailers | 41.7% |
| 402 | Electric Motor, Power Tool, and Related Repairers | 41.6% |
| 403 | Nuclear Medicine Technologists | 41.6% |
| 404 | Social and Human Service Assistants | 41.5% |
| 405 | Gaming Supervisors | 41.4% |
| 406 | Industrial Machinery Mechanics | 41.0% |
| 407 | Reservation and Transportation Ticket Agents and Travel Clerks | 40.8% |
| 408 | Farmworkers, Farm, Ranch, and Aquacultural Animals | 40.8% |
| 409 | Home Appliance Repairers | 40.6% |
| 410 | Dispatchers, Except Police, Fire, and Ambulance | 40.5% |
| 411 | Speech-Language Pathologists | 40.4% |
| 412 | First-Line Supervisors of Farming, Fishing, and Forestry Workers | 40.3% |
| 413 | Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters | 40.2% |
| 414 | Physical Therapist Aides | 40.2% |
| 415 | Lodging Managers | 39.8% |
| 416 | Forensic Science Technicians | 39.6% |
| 417 | Travel Guides | 39.6% |
| 418 | Firefighters | 39.5% |
| 419 | Door-to-Door Sales Workers, News and Street Vendors, and Related Workers | 39.5% |
| 420 | Drafters, All Other | 39.5% |
| 421 | Security Guards | 39.4% |
| 422 | Helpers--Electricians | 39.3% |
| 423 | Couriers and Messengers | 39.2% |
| 424 | Solar Photovoltaic Installers | 39.0% |
| 425 | Respiratory Therapists | 39.0% |
| 426 | Signal and Track Switch Repairers | 39.0% |
| 427 | Gaming and Sports Book Writers and Runners | 38.9% |
| 428 | Tank Car, Truck, and Ship Loaders | 38.7% |
| 429 | Sheet Metal Workers | 38.6% |
| 430 | Material Moving Workers, All Other | 38.5% |
| 431 | Computer Programmers | 38.4% |
| 432 | Training and Development Managers | 38.3% |
| 433 | Industrial Production Managers | 38.3% |
| 434 | Telecommunications Equipment Installers and Repairers, Except Line Installers | 38.2% |
| 435 | Chemical Engineers | 38.1% |
| 436 | Baggage Porters and Bellhops | 38.0% |
| 437 | First-Line Supervisors of Construction Trades and Extraction Workers | 38.0% |
| 438 | Forest and Conservation Technicians | 37.8% |
| 439 | Credit Counselors | 37.7% |
| 440 | Chemists | 37.5% |
| 441 | Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products | 37.3% |
| 442 | Zoologists and Wildlife Biologists | 37.3% |
| 443 | First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand | 37.1% |
| 444 | Physical Therapist Assistants | 37.1% |
| 445 | Database Administrators | 37.1% |
| 446 | Coin, Vending, and Amusement Machine Servicers and Repairers | 37.0% |
| 447 | Eligibility Interviewers, Government Programs | 37.0% |
| 448 | Construction and Building Inspectors | 37.0% |
| 449 | Appraisers and Assessors of Real Estate | 36.9% |
| 450 | Farm and Home Management Advisors | 36.8% |
| 451 | Animal Breeders | 36.7% |
| 452 | Purchasing Managers | 36.4% |
| 453 | Medical and Health Services Managers | 36.3% |
| 454 | Pest Control Workers | 36.3% |
| 455 | Nurse Anesthetists | 36.2% |
| 456 | Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters | 36.2% |
| 457 | Optometrists | 36.2% |
| 458 | Gaming Dealers | 36.1% |
| 459 | First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers | 36.0% |
| 460 | Sales Representatives, Services, All Other | 35.9% |
| 461 | Funeral Attendants | 35.8% |
| 462 | Electrical Power-Line Installers and Repairers | 35.6% |
| 463 | Telecommunications Line Installers and Repairers | 35.6% |
| 464 | Emergency Medical Technicians and Paramedics | 35.5% |
| 465 | Insurance Underwriters | 35.1% |
| 466 | Construction Laborers | 34.9% |
| 467 | Interviewers, Except Eligibility and Loan | 34.8% |
| 468 | Administrative Services Managers | 34.6% |
| 469 | Heating, Air Conditioning, and Refrigeration Mechanics and Installers | 34.5% |
| 470 | Agricultural and Food Science Technicians | 34.4% |
| 471 | Locksmiths and Safe Repairers | 34.0% |
| 472 | Financial Managers | 33.9% |
| 473 | Helpers, Construction Trades, All Other | 33.9% |
| 474 | Tax Examiners and Collectors, and Revenue Agents | 33.8% |
| 475 | Atmospheric and Space Scientists | 33.6% |
| 476 | Photographers | 33.2% |
| 477 | Sales Engineers | 33.1% |
| 478 | First-Line Supervisors of Production and Operating Workers | 32.9% |
| 479 | Forest and Conservation Workers | 32.8% |
| 480 | First-Line Supervisors of Retail Sales Workers | 32.7% |
| 481 | Natural Sciences Managers | 32.3% |
| 482 | Maintenance Workers, Machinery | 32.3% |
| 483 | Social Science Research Assistants | 32.3% |
| 484 | Riggers | 32.2% |
| 485 | Environmental Science and Protection Technicians, Including Health | 31.9% |
| 486 | Physical Therapists | 31.8% |
| 487 | Food Service Managers | 31.8% |
| 488 | Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers | 31.6% |
| 489 | Coaches and Scouts | 31.5% |
| 490 | Rehabilitation Counselors | 31.4% |
| 491 | Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons | 31.4% |
| 492 | Choreographers | 31.2% |
| 493 | Transportation, Storage, and Distribution Managers | 31.2% |
| 494 | Sales and Related Workers, All Other | 30.9% |
| 495 | Farmers, Ranchers, and Other Agricultural Managers | 30.6% |
| 496 | Recreation Workers | 30.6% |
| 497 | Family and General Practitioners | 30.6% |
| 498 | Roofers | 30.5% |
| 499 | Construction and Related Workers, All Other | 30.3% |
| 500 | Therapists, All Other | 30.1% |
| 501 | Occupational Therapy Assistants | 29.8% |
| 502 | Funeral Service Managers | 29.8% |
| 503 | Magnetic Resonance Imaging Technologists | 29.7% |
| 504 | Security and Fire Alarm Systems Installers | 29.7% |
| 505 | Hydrologists | 29.6% |
| 506 | Psychiatric Aides | 29.6% |
| 507 | Customer Service Representatives | 29.3% |
| 508 | Computer Systems Analysts | 29.2% |
| 509 | Fence Erectors | 29.0% |
| 510 | Respiratory Therapy Technicians | 28.9% |
| 511 | Registered Nurses | 28.9% |
| 512 | Social Scientists and Related Workers, All Other | 28.8% |
| 513 | Fine Artists, Including Painters, Sculptors, and Illustrators | 28.8% |
| 514 | Food Scientists and Technologists | 28.6% |
| 515 | Residential Advisors | 28.5% |
| 516 | Biological Scientists, All Other | 28.4% |
| 517 | Managers, All Other | 28.3% |
| 518 | Highway Maintenance Workers | 28.0% |
| 519 | Healthcare Support Workers, All Other | 28.0% |
| 520 | Fire Inspectors and Investigators | 27.8% |
| 521 | Materials Scientists | 27.5% |
| 522 | Mobile Heavy Equipment Mechanics, Except Engines | 27.5% |
| 523 | Engineering Technicians, Except Drafters, All Other | 27.5% |
| 524 | Electrical and Electronics Drafters | 27.3% |
| 525 | Postmasters and Mail Superintendents | 27.3% |
| 526 | Elevator Installers and Repairers | 27.2% |
| 527 | Veterinary Assistants and Laboratory Animal Caretakers | 27.1% |
| 528 | Real Estate Sales Agents | 27.0% |
| 529 | Helpers--Extraction Workers | 27.0% |
| 530 | Athletic Trainers | 26.8% |
| 531 | Physician Assistants | 26.8% |
| 532 | Reinforcing Iron and Rebar Workers | 26.7% |
| 533 | Artists and Related Workers, All Other | 26.6% |
| 534 | Administrative Law Judges, Adjudicators, and Hearing Officers | 26.3% |
| 535 | Mental Health Counselors | 26.1% |
| 536 | Claims Adjusters, Examiners, and Investigators | 26.0% |
| 537 | Software Developers, Systems Software | 25.8% |
| 538 | Proofreaders and Copy Markers | 25.7% |
| 539 | Curators | 25.6% |
| 540 | Building Cleaning Workers, All Other | 25.6% |
| 541 | Computer Hardware Engineers | 25.5% |
| 542 | Medical Scientists, Except Epidemiologists | 25.2% |
| 543 | Maintenance and Repair Workers, General | 25.2% |
| 544 | Occupational Therapists | 25.2% |
| 545 | Chief Executives | 25.0% |
| 546 | Substance Abuse and Behavioral Disorder Counselors | 25.0% |
| 547 | Education, Training, and Library Workers, All Other | 25.0% |
| 548 | Adult Basic and Secondary Education and Literacy Teachers and Instructors | 24.6% |
| 549 | Probation Officers and Correctional Treatment Specialists | 24.4% |
| 550 | Fishers and Related Fishing Workers | 24.2% |
| 551 | Detectives and Criminal Investigators | 24.1% |
| 552 | Mining and Geological Engineers, Including Mining Safety Engineers | 24.0% |
| 553 | Insurance Appraisers, Auto Damage | 23.8% |
| 554 | Biomedical Engineers | 23.8% |
| 555 | Compliance Officers | 23.8% |
| 556 | Loan Officers | 23.7% |
| 557 | Personal Care Aides | 23.6% |
| 558 | Lawyers | 23.5% |
| 559 | Self-Enrichment Education Teachers | 23.3% |
| 560 | Commercial Divers | 23.1% |
| 561 | Dentists, General | 23.1% |
| 562 | Exercise Physiologists | 23.0% |
| 563 | General and Operations Managers | 22.8% |
| 564 | Mechanical Engineering Technicians | 22.7% |
| 565 | Airfield Operations Specialists | 22.6% |
| 566 | Physicians and Surgeons, All Other | 22.6% |
| 567 | Electrical and Electronics Engineering Technicians | 22.6% |
| 568 | Human Resources Specialists | 22.5% |
| 569 | Fashion Designers | 22.5% |
| 570 | Janitors and Cleaners, Except Maids and Housekeeping Cleaners | 22.4% |
| 571 | Health Diagnosing and Treating Practitioners, All Other | 22.4% |
| 572 | Dentists, All Other Specialists | 22.2% |
| 573 | First-Line Supervisors of Office and Administrative Support Workers | 22.1% |
| 574 | Obstetricians and Gynecologists | 21.9% |
| 575 | Animal Control Workers | 21.8% |
| 576 | Computer and Information Research Scientists | 21.7% |
| 577 | Morticians, Undertakers, and Funeral Directors | 21.7% |
| 578 | Credit Analysts | 21.6% |
| 579 | Mathematical Science Teachers, Postsecondary | 21.5% |
| 580 | Electronics Engineers, Except Computer | 21.3% |
| 581 | Judges, Magistrate Judges, and Magistrates | 21.2% |
| 582 | Architectural and Civil Drafters | 21.2% |
| 583 | Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products | 21.1% |
| 584 | Nurse Practitioners | 21.1% |
| 585 | Structural Iron and Steel Workers | 21.1% |
| 586 | Electrical Engineers | 21.1% |
| 587 | Personal Care and Service Workers, All Other | 21.0% |
| 588 | Middle School Teachers, Except Special and Career/Technical Education | 21.0% |
| 589 | Private Detectives and Investigators | 20.9% |
| 590 | Counselors, All Other | 20.7% |
| 591 | Computer Occupations, All Other | 20.7% |
| 592 | Agricultural Inspectors | 20.6% |
| 593 | Career/Technical Education Teachers, Middle School | 20.6% |
| 594 | Art, Drama, and Music Teachers, Postsecondary | 20.5% |
| 595 | Civil Engineering Technicians | 20.5% |
| 596 | Sociology Teachers, Postsecondary | 20.4% |
| 597 | Compensation and Benefits Managers | 20.4% |
| 598 | Advertising Sales Agents | 20.1% |
| 599 | Anesthesiologists | 20.1% |
| 600 | Foreign Language and Literature Teachers, Postsecondary | 20.1% |
| 601 | Environmental Scientists and Specialists, Including Health | 20.0% |
| 602 | Community and Social Service Specialists, All Other | 19.9% |
| 603 | Social Workers, All Other | 19.9% |
| 604 | Teacher Assistants | 19.9% |
| 605 | Oral and Maxillofacial Surgeons | 19.8% |
| 606 | Substitute Teachers | 19.8% |
| 607 | Geographers | 19.8% |
| 608 | Health Educators | 19.7% |
| 609 | Radio and Television Announcers | 19.7% |
| 610 | Recreation and Fitness Studies Teachers, Postsecondary | 19.7% |
| 611 | First-Line Supervisors of Non-Retail Sales Workers | 19.6% |
| 612 | Helpers--Installation, Maintenance, and Repair Workers | 19.6% |
| 613 | Secondary School Teachers, Except Special and Career/Technical Education | 19.6% |
| 614 | Psychiatric Technicians | 19.6% |
| 615 | Area, Ethnic, and Cultural Studies Teachers, Postsecondary | 19.5% |
| 616 | Child, Family, and School Social Workers | 19.4% |
| 617 | Childcare Workers | 19.4% |
| 618 | Physicists | 19.3% |
| 619 | Electro-Mechanical Technicians | 19.3% |
| 620 | Police and Sheriff's Patrol Officers | 19.2% |
| 621 | Petroleum Engineers | 19.1% |
| 622 | Internists, General | 18.9% |
| 623 | Art Directors | 18.8% |
| 624 | Economics Teachers, Postsecondary | 18.8% |
| 625 | History Teachers, Postsecondary | 18.7% |
| 626 | Computer and Information Systems Managers | 18.7% |
| 627 | Criminal Justice and Law Enforcement Teachers, Postsecondary | 18.6% |
| 628 | Communications Teachers, Postsecondary | 18.6% |
| 629 | Teachers and Instructors, All Other, Except Substitute Teachers | 18.5% |
| 630 | Marine Engineers and Naval Architects | 18.5% |
| 631 | Home Economics Teachers, Postsecondary | 18.3% |
| 632 | Philosophy and Religion Teachers, Postsecondary | 18.1% |
| 633 | Career/Technical Education Teachers, Secondary School | 18.1% |
| 634 | Recreational Therapists | 18.0% |
| 635 | Materials Engineers | 18.0% |
| 636 | Maids and Housekeeping Cleaners | 17.9% |
| 637 | Embalmers | 17.9% |
| 638 | Pediatricians, General | 17.9% |
| 639 | Education Administrators, All Other | 17.7% |
| 640 | Health and Safety Engineers, Except Mining Safety Engineers and Inspectors | 17.6% |
| 641 | Podiatrists | 17.6% |
| 642 | Business Operations Specialists, All Other | 17.5% |
| 643 | Health Specialties Teachers, Postsecondary | 17.5% |
| 644 | Architectural and Engineering Managers | 17.4% |
| 645 | Political Science Teachers, Postsecondary | 17.4% |
| 646 | Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary | 17.4% |
| 647 | Merchandise Displayers and Window Trimmers | 17.3% |
| 648 | Film and Video Editors | 17.3% |
| 649 | Healthcare Practitioners and Technical Workers, All Other | 17.3% |
| 650 | Psychology Teachers, Postsecondary | 17.3% |
| 651 | Prosthodontists | 17.2% |
| 652 | Engineers, All Other | 17.0% |
| 653 | Media and Communication Workers, All Other | 17.0% |
| 654 | Construction Managers | 16.9% |
| 655 | Education Administrators, Preschool and Childcare Center/Program | 16.9% |
| 656 | Set and Exhibit Designers | 16.8% |
| 657 | Mechanical Engineers | 16.7% |
| 658 | Transportation Inspectors | 16.6% |
| 659 | Demonstrators and Product Promoters | 16.6% |
| 660 | Agricultural Sciences Teachers, Postsecondary | 16.5% |
| 661 | Engineering Teachers, Postsecondary | 16.4% |
| 662 | Biological Science Teachers, Postsecondary | 16.4% |
| 663 | Anthropology and Archeology Teachers, Postsecondary | 16.4% |
| 664 | Interpreters and Translators | 16.4% |
| 665 | Education Administrators, Postsecondary | 16.3% |
| 666 | Cleaners of Vehicles and Equipment | 16.2% |
| 667 | Licensed Practical and Licensed Vocational Nurses | 16.1% |
| 668 | Genetic Counselors | 16.0% |
| 669 | Postsecondary Teachers, All Other | 16.0% |
| 670 | Opticians, Dispensing | 15.7% |
| 671 | Property, Real Estate, and Community Association Managers | 15.7% |
| 672 | Court Reporters | 15.7% |
| 673 | Social Sciences Teachers, Postsecondary, All Other | 15.6% |
| 674 | Chemistry Teachers, Postsecondary | 15.6% |
| 675 | Elementary School Teachers, Except Special Education | 15.4% |
| 676 | Education Teachers, Postsecondary | 15.2% |
| 677 | Geography Teachers, Postsecondary | 15.2% |
| 678 | Statisticians | 15.1% |
| 679 | Reporters and Correspondents | 14.9% |
| 680 | Landscape Architects | 14.7% |
| 681 | Environmental Science Teachers, Postsecondary | 14.7% |
| 682 | Crossing Guards | 14.7% |
| 683 | Life Scientists, All Other | 14.7% |
| 684 | Sociologists | 14.7% |
| 685 | Actuaries | 14.6% |
| 686 | Community Health Workers | 14.6% |
| 687 | Forestry and Conservation Science Teachers, Postsecondary | 14.3% |
| 688 | Graduate Teaching Assistants | 14.1% |
| 689 | Educational, Guidance, School, and Vocational Counselors | 14.0% |
| 690 | Cost Estimators | 14.0% |
| 691 | Environmental Engineering Technicians | 13.9% |
| 692 | Designers, All Other | 13.9% |
| 693 | Human Resources Managers | 13.9% |
| 694 | Education Administrators, Elementary and Secondary School | 13.8% |
| 695 | Financial Examiners | 13.8% |
| 696 | Nursing Instructors and Teachers, Postsecondary | 13.8% |
| 697 | Architecture Teachers, Postsecondary | 13.8% |
| 698 | English Language and Literature Teachers, Postsecondary | 13.7% |
| 699 | Aerospace Engineers | 13.6% |
| 700 | Civil Engineers | 13.5% |
| 701 | Advertising and Promotions Managers | 13.4% |
| 702 | Writers and Authors | 13.4% |
| 703 | Umpires, Referees, and Other Sports Officials | 13.3% |
| 704 | Marketing Managers | 13.3% |
| 705 | Surgeons | 13.3% |
| 706 | Producers and Directors | 13.2% |
| 707 | Dental Hygienists | 13.2% |
| 708 | Fundraisers | 13.1% |
| 709 | Broadcast News Analysts | 13.0% |
| 710 | Market Research Analysts and Marketing Specialists | 12.9% |
| 711 | Public Address System and Other Announcers | 12.8% |
| 712 | Marriage and Family Therapists | 12.8% |
| 713 | Graphic Designers | 12.7% |
| 714 | Nonfarm Animal Caretakers | 12.7% |
| 715 | Orderlies | 12.5% |
| 716 | Interior Designers | 12.4% |
| 717 | Personal Financial Advisors | 12.3% |
| 718 | Accountants and Auditors | 12.2% |
| 719 | Environmental Engineers | 12.0% |
| 720 | Veterinarians | 11.8% |
| 721 | Clinical, Counseling, and School Psychologists | 11.8% |
| 722 | Vocational Education Teachers, Postsecondary | 11.7% |
| 723 | Physics Teachers, Postsecondary | 11.6% |
| 724 | Agents and Business Managers of Artists, Performers, and Athletes | 11.5% |
| 725 | Buyers and Purchasing Agents, Farm Products | 11.5% |
| 726 | Fitness Trainers and Aerobics Instructors | 11.3% |
| 727 | Industrial Engineers | 11.3% |
| 728 | Arbitrators, Mediators, and Conciliators | 11.3% |
| 729 | Nurse Midwives | 11.2% |
| 730 | Special Education Teachers, Secondary School | 11.2% |
| 731 | Special Education Teachers, All Other | 11.2% |
| 732 | Healthcare Social Workers | 11.2% |
| 733 | Foresters | 11.0% |
| 734 | Orthodontists | 11.0% |
| 735 | Psychologists, All Other | 10.9% |
| 736 | Nuclear Engineers | 10.9% |
| 737 | Home Health Aides | 10.8% |
| 738 | Architects, Except Landscape and Naval | 10.8% |
| 739 | Computer Science Teachers, Postsecondary | 10.7% |
| 740 | Labor Relations Specialists | 10.7% |
| 741 | Public Relations Specialists | 10.7% |
| 742 | Financial Analysts | 10.6% |
| 743 | Social Work Teachers, Postsecondary | 10.6% |
| 744 | Biochemists and Biophysicists | 10.2% |
| 745 | Special Education Teachers, Kindergarten and Elementary School | 10.2% |
| 746 | Special Education Teachers, Middle School | 10.2% |
| 747 | Kindergarten Teachers, Except Special Education | 10.0% |
| 748 | Orthotists and Prosthetists | 10.0% |
| 749 | Mechanical Drafters | 9.7% |
| 750 | Business Teachers, Postsecondary | 9.7% |
| 751 | Editors | 9.5% |
| 752 | Massage Therapists | 9.5% |
| 753 | Helpers--Roofers | 9.5% |
| 754 | Law Teachers, Postsecondary | 9.5% |
| 755 | Special Education Teachers, Preschool | 9.3% |
| 756 | Landscaping and Groundskeeping Workers | 9.2% |
| 757 | Hoist and Winch Operators | 9.1% |
| 758 | Epidemiologists | 9.0% |
| 759 | Emergency Management Directors | 8.9% |
| 760 | Mathematicians | 8.9% |
| 761 | Economists | 8.8% |
| 762 | Mental Health and Substance Abuse Social Workers | 8.8% |
| 763 | Conservation Scientists | 8.7% |
| 764 | Meeting, Convention, and Event Planners | 8.7% |
| 765 | Mathematical Science Occupations, All Other | 8.4% |
| 766 | Library Science Teachers, Postsecondary | 8.4% |
| 767 | Preschool Teachers, Except Special Education | 8.3% |
| 768 | Software Developers, Applications | 8.2% |
| 769 | Industrial-Organizational Psychologists | 7.7% |
| 770 | Occupational Health and Safety Specialists | 7.6% |
| 771 | Psychiatrists | 7.5% |
| 772 | Musicians and Singers | 7.4% |
| 773 | Industrial Engineering Technicians | 7.4% |
| 774 | Sales Managers | 7.4% |
| 775 | Political Scientists | 7.3% |
| 776 | Archivists | 7.2% |
| 777 | Refuse and Recyclable Material Collectors | 7.2% |
| 778 | Survey Researchers | 7.0% |
| 779 | Laborers and Freight, Stock, and Material Movers, Hand | 6.7% |
| 780 | Farm Labor Contractors | 6.4% |
| 781 | Compensation, Benefits, and Job Analysis Specialists | 5.7% |
| 782 | Tree Trimmers and Pruners | 5.2% |
| 783 | Social and Community Service Managers | 5.2% |
| 784 | Budget Analysts | 5.2% |
| 785 | Roustabouts, Oil and Gas | 5.0% |
| 786 | Anthropologists and Archeologists | 4.6% |
| 787 | Wholesale and Retail Buyers, Except Farm Products | 4.6% |
| 788 | Management Analysts | 4.1% |
| 789 | Legislators | 4.0% |
| 790 | Entertainers and Performers, Sports and Related Workers, All Other | 3.7% |
| 791 | Chiropractors | 3.5% |
| 792 | Operations Research Analysts | 3.5% |
| 793 | Fish and Game Wardens | 3.5% |
| 794 | Instructional Coordinators | 3.3% |
| 795 | Agricultural Engineers | 3.2% |
| 796 | Commercial and Industrial Designers | 3.2% |
| 797 | Public Relations and Fundraising Managers | 3.0% |
| 798 | Soil and Plant Scientists | 3.0% |
| 799 | Transit and Railroad Police | 2.7% |
| 800 | Urban and Regional Planners | 2.5% |
| 801 | Training and Development Specialists | 2.3% |
| 802 | Logisticians | 2.1% |
| 803 | Purchasing Agents, Except Wholesale, Retail, and Farm Products | 2.0% |
| 804 | Multimedia Artists and Animators | 1.9% |
| 805 | Financial Specialists, All Other | 1.0% |
| 806 | Actors | 0.8% |
| 807 | Ambulance Drivers and Attendants, Except Emergency Medical Technicians | 0% |
| 808 | Roof Bolters, Mining | 0% |
| 809 | Models | 0% |
| 810 | Animal Trainers | 0% |
| 811 | Music Directors and Composers | 0% |
| 812 | Dancers | 0% |
| 813 | Athletes and Sports Competitors | 0% |
| 814 | Religious Workers, All Other | 0% |
| 815 | Directors, Religious Activities and Education | 0% |
| 816 | Clergy | 0% |
| 817 | Historians | 0% |
| 818 | Astronomers | 0% |
| 819 | Animal Scientists | 0% |
| 820 | Mathematical Technicians | 0% |
| *Source: McKinsey Global Institute* | | |

Appendix B. State average automation potentials

|  |  |  |
| --- | --- | --- |
| **Rank** | **State** | **Average automation potential** |
| 1 | Indiana | 48.7% |
| 2 | Kentucky | 48.4% |
| 3 | South Dakota | 48.3% |
| 4 | Iowa | 48.0% |
| 5 | Nevada | 48.0% |
| 6 | Arkansas | 48.0% |
| 7 | Alabama | 47.9% |
| 8 | Wyoming | 47.8% |
| 9 | Mississippi | 47.7% |
| 10 | Wisconsin | 47.5% |
| 11 | Nebraska | 47.5% |
| 12 | Tennessee | 47.3% |
| 13 | Ohio | 47.2% |
| 14 | Montana | 47.0% |
| 15 | Oklahoma | 46.9% |
| 16 | West Virginia | 46.9% |
| 17 | Kansas | 46.8% |
| 18 | North Carolina | 46.7% |
| 19 | North Dakota | 46.7% |
| 20 | South Carolina | 46.6% |
| 21 | Michigan | 46.5% |
| 22 | Missouri | 46.5% |
| 23 | Maine | 46.5% |
| 24 | Louisiana | 46.5% |
| 25 | Texas | 46.5% |
| 26 | Idaho | 46.4% |
| 27 | Florida | 46.3% |
| 28 | New Hampshire | 46.1% |
| 29 | Oregon | 46.1% |
| 30 | Rhode Island | 46.0% |
| 31 | Pennsylvania | 45.9% |
| 32 | Alaska | 45.9% |
| 33 | Hawaii | 45.8% |
| 34 | Georgia | 45.8% |
| 35 | Utah | 45.6% |
| 36 | Delaware | 45.6% |
| 37 | Illinois | 45.6% |
| 38 | California | 45.2% |
| 39 | Vermont | 45.1% |
| 40 | Minnesota | 45.0% |
| 41 | Arizona | 45.0% |
| 42 | Washington | 44.9% |
| 43 | Colorado | 44.4% |
| 44 | New Mexico | 44.3% |
| 45 | New Jersey | 44.1% |
| 46 | Virginia | 44.0% |
| 47 | Connecticut | 43.5% |
| 48 | Maryland | 43.2% |
| 49 | Massachusetts | 42.9% |
| 50 | New York | 42.4% |
| *Note: Averages weighted by occupational employment shares* | | |
| *Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data* | | |

Appendix C. Metropolitan areas’ automation potentials

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| --- | --- | --- |
| **Rank** | **Metropolitan area** | **Average automation potential** |
| 1 | Dalton, GA | 56.0% |
| 2 | Kokomo, IN | 54.7% |
| 3 | Elkhart-Goshen, IN | 54.6% |
| 4 | Hickory-Lenoir-Morganton, NC | 52.6% |
| 5 | Grand Island, NE | 52.4% |
| 6 | Burlington, NC | 52.2% |
| 7 | Harrisonburg, VA | 52.0% |
| 8 | Gettysburg, PA | 51.6% |
| 9 | Sioux City, IA-NE-SD | 51.6% |
| 10 | Gadsden, AL | 51.5% |
| 11 | Fort Smith, AR-OK | 51.5% |
| 12 | Morristown, TN | 51.3% |
| 13 | Michigan City-La Porte, IN | 51.0% |
| 14 | Odessa, TX | 50.9% |
| 15 | Florence-Muscle Shoals, AL | 50.9% |
| 16 | St. Joseph, MO-KS | 50.9% |
| 17 | Lima, OH | 50.8% |
| 18 | Joplin, MO | 50.7% |
| 19 | Muskegon, MI | 50.7% |
| 20 | Sheboygan, WI | 50.6% |
| 21 | Terre Haute, IN | 50.6% |
| 22 | Auburn-Opelika, AL | 50.5% |
| 23 | Mansfield, OH | 50.4% |
| 24 | Columbus, IN | 50.3% |
| 25 | Gainesville, GA | 50.2% |
| 26 | Wausau, WI | 50.1% |
| 27 | Cleveland, TN | 50.1% |
| 28 | Lebanon, PA | 50.1% |
| 29 | Greeley, CO | 50.1% |
| 30 | Lafayette-West Lafayette, IN | 50.1% |
| 31 | Albany, OR | 50.1% |
| 32 | Anniston-Oxford-Jacksonville, AL | 50.1% |
| 33 | Weirton-Steubenville, WV-OH | 50.0% |
| 34 | Danville, IL | 50.0% |
| 35 | Lewiston, ID-WA | 49.9% |
| 36 | Bowling Green, KY | 49.8% |
| 37 | Decatur, AL | 49.8% |
| 38 | Merced, CA | 49.7% |
| 39 | Canton-Massillon, OH | 49.7% |
| 40 | Longview, WA | 49.7% |
| 41 | Decatur, IL | 49.6% |
| 42 | Modesto, CA | 49.6% |
| 43 | Tuscaloosa, AL | 49.5% |
| 44 | Salisbury, MD-DE | 49.5% |
| 45 | Longview, TX | 49.5% |
| 46 | Springfield, OH | 49.4% |
| 47 | St. Cloud, MN | 49.4% |
| 48 | College Station-Bryan, TX | 49.4% |
| 49 | Oshkosh-Neenah, WI | 49.4% |
| 50 | Yakima, WA | 49.4% |
| 51 | Evansville, IN-KY | 49.4% |
| 52 | Rocky Mount, NC | 49.4% |
| 53 | The Villages, FL | 49.3% |
| 54 | Logan, UT-ID | 49.3% |
| 55 | Racine, WI | 49.3% |
| 56 | Owensboro, KY | 49.3% |
| 57 | Fond du Lac, WI | 49.2% |
| 58 | Houma-Thibodaux, LA | 49.2% |
| 59 | Wenatchee, WA | 49.2% |
| 60 | Waterloo-Cedar Falls, IA | 49.1% |
| 61 | Goldsboro, NC | 49.1% |
| 62 | Kingsport-Bristol-Bristol, TN-VA | 49.1% |
| 63 | Lake Havasu City-Kingman, AZ | 49.0% |
| 64 | Lancaster, PA | 49.0% |
| 65 | Toledo, OH | 49.0% |
| 66 | Monroe, MI | 48.9% |
| 67 | Fort Wayne, IN | 48.9% |
| 68 | Williamsport, PA | 48.8% |
| 69 | Niles-Benton Harbor, MI | 48.8% |
| 70 | Bay City, MI | 48.8% |
| 71 | Blacksburg-Christiansburg-Radford, VA | 48.8% |
| 72 | Texarkana, TX-AR | 48.7% |
| 73 | Muncie, IN | 48.7% |
| 74 | Daphne-Fairhope-Foley, AL | 48.7% |
| 75 | Green Bay, WI | 48.7% |
| 76 | Janesville-Beloit, WI | 48.7% |
| 77 | Vineland-Bridgeton, NJ | 48.7% |
| 78 | Staunton-Waynesboro, VA | 48.7% |
| 79 | Rome, GA | 48.6% |
| 80 | Youngstown-Warren-Boardman, OH-PA | 48.6% |
| 81 | Appleton, WI | 48.6% |
| 82 | Hanford-Corcoran, CA | 48.6% |
| 83 | Amarillo, TX | 48.6% |
| 84 | Davenport-Moline-Rock Island, IA-IL | 48.6% |
| 85 | Kankakee, IL | 48.6% |
| 86 | Greensboro-High Point, NC | 48.5% |
| 87 | Lakeland-Winter Haven, FL | 48.5% |
| 88 | Dothan, AL | 48.5% |
| 89 | Erie, PA | 48.5% |
| 90 | Mount Vernon-Anacortes, WA | 48.4% |
| 91 | Saginaw, MI | 48.4% |
| 92 | Victoria, TX | 48.4% |
| 93 | Myrtle Beach-Conway-North Myrtle Beach, SC-NC | 48.4% |
| 94 | Altoona, PA | 48.4% |
| 95 | Beaumont-Port Arthur, TX | 48.4% |
| 96 | Medford, OR | 48.4% |
| 97 | Jacksonville, NC | 48.4% |
| 98 | Midland, TX | 48.4% |
| 99 | Stockton-Lodi, CA | 48.3% |
| 100 | Ocean City, NJ | 48.3% |
| 101 | York-Hanover, PA | 48.3% |
| 102 | Lynchburg, VA | 48.3% |
| 103 | Kahului-Wailuku-Lahaina, HI | 48.3% |
| 104 | Cape Girardeau, MO-IL | 48.3% |
| 105 | Jonesboro, AR | 48.3% |
| 106 | Madera, CA | 48.3% |
| 107 | Visalia-Porterville, CA | 48.3% |
| 108 | Dubuque, IA | 48.2% |
| 109 | Farmington, NM | 48.2% |
| 110 | East Stroudsburg, PA | 48.2% |
| 111 | Mobile, AL | 48.2% |
| 112 | Sherman-Denison, TX | 48.2% |
| 113 | Las Vegas-Henderson-Paradise, NV | 48.2% |
| 114 | Spartanburg, SC | 48.2% |
| 115 | Jackson, TN | 48.2% |
| 116 | Springfield, MO | 48.1% |
| 117 | Clarksville, TN-KY | 48.1% |
| 118 | Punta Gorda, FL | 48.1% |
| 119 | Winston-Salem, NC | 48.1% |
| 120 | Fayetteville-Springdale-Rogers, AR-MO | 48.0% |
| 121 | Rockford, IL | 48.0% |
| 122 | Asheville, NC | 48.0% |
| 123 | Elmira, NY | 48.0% |
| 124 | Grand Rapids-Wyoming, MI | 48.0% |
| 125 | Grants Pass, OR | 48.0% |
| 126 | Waco, TX | 48.0% |
| 127 | Valdosta, GA | 48.0% |
| 128 | Bellingham, WA | 47.9% |
| 129 | Gulfport-Biloxi-Pascagoula, MS | 47.9% |
| 130 | Carbondale-Marion, IL | 47.9% |
| 131 | South Bend-Mishawaka, IN-MI | 47.9% |
| 132 | Ocala, FL | 47.9% |
| 133 | Hot Springs, AR | 47.9% |
| 134 | Casper, WY | 47.9% |
| 135 | Louisville/Jefferson County, KY-IN | 47.9% |
| 136 | San Angelo, TX | 47.9% |
| 137 | St. George, UT | 47.8% |
| 138 | Reading, PA | 47.8% |
| 139 | Scranton--Wilkes-Barre--Hazleton, PA | 47.8% |
| 140 | Walla Walla, WA | 47.8% |
| 141 | Lawton, OK | 47.8% |
| 142 | Fresno, CA | 47.8% |
| 143 | Jackson, MI | 47.8% |
| 144 | La Crosse-Onalaska, WI-MN | 47.8% |
| 145 | Sebastian-Vero Beach, FL | 47.7% |
| 146 | Eau Claire, WI | 47.7% |
| 147 | Rapid City, SD | 47.7% |
| 148 | Lake Charles, LA | 47.7% |
| 149 | Cape Coral-Fort Myers, FL | 47.7% |
| 150 | Eugene, OR | 47.7% |
| 151 | Lafayette, LA | 47.7% |
| 152 | Naples-Immokalee-Marco Island, FL | 47.6% |
| 153 | Dover, DE | 47.6% |
| 154 | Deltona-Daytona Beach-Ormond Beach, FL | 47.6% |
| 155 | Salinas, CA | 47.6% |
| 156 | Manhattan, KS | 47.6% |
| 157 | Santa Cruz-Watsonville, CA | 47.6% |
| 158 | Lubbock, TX | 47.6% |
| 159 | Riverside-San Bernardino-Ontario, CA | 47.6% |
| 160 | Flint, MI | 47.6% |
| 161 | Coeur d'Alene, ID | 47.6% |
| 162 | Lawrence, KS | 47.5% |
| 163 | Chattanooga, TN-GA | 47.5% |
| 164 | Elizabethtown-Fort Knox, KY | 47.5% |
| 165 | Wichita, KS | 47.5% |
| 166 | Bloomington, IN | 47.4% |
| 167 | Chambersburg-Waynesboro, PA | 47.4% |
| 168 | El Paso, TX | 47.4% |
| 169 | Lewiston-Auburn, ME | 47.4% |
| 170 | Billings, MT | 47.3% |
| 171 | Pine Bluff, AR | 47.3% |
| 172 | Corpus Christi, TX | 47.3% |
| 173 | Bloomsburg-Berwick, PA | 47.3% |
| 174 | Sebring, FL | 47.3% |
| 175 | Tulsa, OK | 47.3% |
| 176 | Athens-Clarke County, GA | 47.3% |
| 177 | Sioux Falls, SD | 47.3% |
| 178 | Bend-Redmond, OR | 47.2% |
| 179 | Lexington-Fayette, KY | 47.2% |
| 180 | Panama City, FL | 47.2% |
| 181 | Kalamazoo-Portage, MI | 47.2% |
| 182 | Greenville-Anderson-Mauldin, SC | 47.2% |
| 183 | Wheeling, WV-OH | 47.1% |
| 184 | Johnson City, TN | 47.1% |
| 185 | Missoula, MT | 47.1% |
| 186 | Brunswick, GA | 47.1% |
| 187 | Akron, OH | 47.1% |
| 188 | Wichita Falls, TX | 47.0% |
| 189 | Huntington-Ashland, WV-KY-OH | 47.0% |
| 190 | Parkersburg-Vienna, WV | 46.9% |
| 191 | Winchester, VA-WV | 46.9% |
| 192 | Bakersfield, CA | 46.9% |
| 193 | Napa, CA | 46.9% |
| 194 | Homosassa Springs, FL | 46.9% |
| 195 | Hammond, LA | 46.9% |
| 196 | Abilene, TX | 46.9% |
| 197 | Prescott, AZ | 46.9% |
| 198 | Santa Rosa, CA | 46.9% |
| 199 | Sumter, SC | 46.9% |
| 200 | Beckley, WV | 46.9% |
| 201 | Reno, NV | 46.8% |
| 202 | Iowa City, IA | 46.8% |
| 203 | Knoxville, TN | 46.8% |
| 204 | Mankato-North Mankato, MN | 46.8% |
| 205 | Wilmington, NC | 46.8% |
| 206 | Cincinnati, OH-KY-IN | 46.8% |
| 207 | Savannah, GA | 46.7% |
| 208 | Ogden-Clearfield, UT | 46.7% |
| 209 | Roanoke, VA | 46.7% |
| 210 | Greenville, NC | 46.7% |
| 211 | Hattiesburg, MS | 46.7% |
| 212 | Cumberland, MD-WV | 46.7% |
| 213 | North Port-Sarasota-Bradenton, FL | 46.7% |
| 214 | Grand Forks, ND-MN | 46.7% |
| 215 | Champaign-Urbana, IL | 46.7% |
| 216 | Vallejo-Fairfield, CA | 46.7% |
| 217 | Tyler, TX | 46.6% |
| 218 | Flagstaff, AZ | 46.6% |
| 219 | Allentown-Bethlehem-Easton, PA-NJ | 46.6% |
| 220 | Port St. Lucie, FL | 46.6% |
| 221 | New Bern, NC | 46.6% |
| 222 | Florence, SC | 46.6% |
| 223 | Oxnard-Thousand Oaks-Ventura, CA | 46.6% |
| 224 | Portland-South Portland, ME | 46.5% |
| 225 | Cleveland-Elyria, OH | 46.5% |
| 226 | Redding, CA | 46.5% |
| 227 | Chico, CA | 46.5% |
| 228 | Columbia, MO | 46.5% |
| 229 | Battle Creek, MI | 46.5% |
| 230 | Santa Maria-Santa Barbara, CA | 46.5% |
| 231 | Nashville-Davidson--Murfreesboro--Franklin, TN | 46.5% |
| 232 | Bangor, ME | 46.5% |
| 233 | Dallas-Fort Worth-Arlington, TX | 46.5% |
| 234 | Montgomery, AL | 46.4% |
| 235 | New Orleans-Metairie, LA | 46.4% |
| 236 | Hagerstown-Martinsburg, MD-WV | 46.4% |
| 237 | Lincoln, NE | 46.4% |
| 238 | Johnstown, PA | 46.4% |
| 239 | Grand Junction, CO | 46.3% |
| 240 | Laredo, TX | 46.3% |
| 241 | Houston-The Woodlands-Sugar Land, TX | 46.3% |
| 242 | Orlando-Kissimmee-Sanford, FL | 46.3% |
| 243 | Birmingham-Hoover, AL | 46.3% |
| 244 | State College, PA | 46.3% |
| 245 | Killeen-Temple, TX | 46.3% |
| 246 | San Luis Obispo-Paso Robles-Arroyo Grande, CA | 46.3% |
| 247 | Memphis, TN-MS-AR | 46.3% |
| 248 | Atlantic City-Hammonton, NJ | 46.3% |
| 249 | Fayetteville, NC | 46.3% |
| 250 | Cheyenne, WY | 46.2% |
| 251 | Pensacola-Ferry Pass-Brent, FL | 46.2% |
| 252 | Miami-Fort Lauderdale-West Palm Beach, FL | 46.2% |
| 253 | Yuba City, CA | 46.2% |
| 254 | El Centro, CA | 46.2% |
| 255 | Spokane-Spokane Valley, WA | 46.2% |
| 256 | Hilton Head Island-Bluffton-Beaufort, SC | 46.2% |
| 257 | Columbus, GA-AL | 46.2% |
| 258 | Carson City, NV | 46.2% |
| 259 | Crestview-Fort Walton Beach-Destin, FL | 46.1% |
| 260 | Jacksonville, FL | 46.1% |
| 261 | Idaho Falls, ID | 46.1% |
| 262 | Dayton, OH | 46.1% |
| 263 | Providence-Warwick, RI-MA | 46.1% |
| 264 | Fairbanks, AK | 46.1% |
| 265 | Omaha-Council Bluffs, NE-IA | 46.1% |
| 266 | Macon, GA | 46.1% |
| 267 | Great Falls, MT | 46.1% |
| 268 | San Antonio-New Braunfels, TX | 46.0% |
| 269 | Augusta-Richmond County, GA-SC | 46.0% |
| 270 | Pueblo, CO | 45.9% |
| 271 | Kennewick-Richland, WA | 45.9% |
| 272 | Morgantown, WV | 45.9% |
| 273 | Fort Collins, CO | 45.9% |
| 274 | Pittsburgh, PA | 45.9% |
| 275 | Indianapolis-Carmel-Anderson, IN | 45.9% |
| 276 | Baton Rouge, LA | 45.9% |
| 277 | Shreveport-Bossier City, LA | 45.9% |
| 278 | Tampa-St. Petersburg-Clearwater, FL | 45.9% |
| 279 | Fargo, ND-MN | 45.8% |
| 280 | Oklahoma City, OK | 45.8% |
| 281 | St. Louis, MO-IL | 45.7% |
| 282 | Monroe, LA | 45.7% |
| 283 | Charlotte-Concord-Gastonia, NC-SC | 45.7% |
| 284 | Jefferson City, MO | 45.7% |
| 285 | Buffalo-Cheektowaga-Niagara Falls, NY | 45.7% |
| 286 | Charleston-North Charleston, SC | 45.7% |
| 287 | Syracuse, NY | 45.6% |
| 288 | Yuma, AZ | 45.6% |
| 289 | Manchester-Nashua, NH | 45.6% |
| 290 | Barnstable Town, MA | 45.6% |
| 291 | Los Angeles-Long Beach-Anaheim, CA | 45.6% |
| 292 | Hinesville, GA | 45.6% |
| 293 | Cedar Rapids, IA | 45.6% |
| 294 | Virginia Beach-Norfolk-Newport News, VA-NC | 45.5% |
| 295 | Duluth, MN-WI | 45.5% |
| 296 | Palm Bay-Melbourne-Titusville, FL | 45.5% |
| 297 | Salem, OR | 45.5% |
| 298 | Ames, IA | 45.5% |
| 299 | Milwaukee-Waukesha-West Allis, WI | 45.5% |
| 300 | Glens Falls, NY | 45.5% |
| 301 | Bremerton-Silverdale, WA | 45.5% |
| 302 | Detroit-Warren-Dearborn, MI | 45.4% |
| 303 | Kingston, NY | 45.4% |
| 304 | Albany, GA | 45.3% |
| 305 | Chicago-Naperville-Elgin, IL-IN-WI | 45.3% |
| 306 | Utica-Rome, NY | 45.2% |
| 307 | Watertown-Fort Drum, NY | 45.2% |
| 308 | Kansas City, MO-KS | 45.2% |
| 309 | Alexandria, LA | 45.1% |
| 310 | Corvallis, OR | 45.1% |
| 311 | Charleston, WV | 45.1% |
| 312 | Provo-Orem, UT | 45.1% |
| 313 | Harrisburg-Carlisle, PA | 45.1% |
| 314 | Little Rock-North Little Rock-Conway, AR | 45.1% |
| 315 | Urban Honolulu, HI | 45.1% |
| 316 | Rochester, MN | 45.1% |
| 317 | Burlington-South Burlington, VT | 45.1% |
| 318 | San Diego-Carlsbad, CA | 45.0% |
| 319 | Lansing-East Lansing, MI | 45.0% |
| 320 | Columbia, SC | 45.0% |
| 321 | Portland-Vancouver-Hillsboro, OR-WA | 45.0% |
| 322 | Anchorage, AK | 44.9% |
| 323 | Norwich-New London, CT | 44.9% |
| 324 | Warner Robins, GA | 44.8% |
| 325 | Jackson, MS | 44.8% |
| 326 | Phoenix-Mesa-Scottsdale, AZ | 44.8% |
| 327 | Peoria, IL | 44.8% |
| 328 | Binghamton, NY | 44.8% |
| 329 | Boise City, ID | 44.8% |
| 330 | Columbus, OH | 44.7% |
| 331 | Tucson, AZ | 44.7% |
| 332 | Atlanta-Sandy Springs-Roswell, GA | 44.7% |
| 333 | Topeka, KS | 44.6% |
| 334 | Salt Lake City, UT | 44.6% |
| 335 | Richmond, VA | 44.6% |
| 336 | Gainesville, FL | 44.6% |
| 337 | Bloomington, IL | 44.6% |
| 338 | Rochester, NY | 44.5% |
| 339 | Midland, MI | 44.5% |
| 340 | Des Moines-West Des Moines, IA | 44.5% |
| 341 | Ithaca, NY | 44.4% |
| 342 | Worcester, MA-CT | 44.4% |
| 343 | Austin-Round Rock, TX | 44.3% |
| 344 | McAllen-Edinburg-Mission, TX | 44.3% |
| 345 | Springfield, IL | 44.2% |
| 346 | Pocatello, ID | 44.2% |
| 347 | New Haven-Milford, CT | 44.2% |
| 348 | Ann Arbor, MI | 44.1% |
| 349 | Madison, WI | 44.0% |
| 350 | Santa Fe, NM | 44.0% |
| 351 | Pittsfield, MA | 43.9% |
| 352 | Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 43.9% |
| 353 | Minneapolis-St. Paul-Bloomington, MN-WI | 43.9% |
| 354 | Sacramento--Roseville--Arden-Arcade, CA | 43.8% |
| 355 | Las Cruces, NM | 43.8% |
| 356 | Springfield, MA | 43.7% |
| 357 | Colorado Springs, CO | 43.6% |
| 358 | Seattle-Tacoma-Bellevue, WA | 43.6% |
| 359 | Denver-Aurora-Lakewood, CO | 43.6% |
| 360 | Bismarck, ND | 43.6% |
| 361 | Olympia-Tumwater, WA | 43.6% |
| 362 | Hartford-West Hartford-East Hartford, CT | 43.5% |
| 363 | Charlottesville, VA | 43.4% |
| 364 | Baltimore-Columbia-Towson, MD | 43.4% |
| 365 | Raleigh, NC | 43.3% |
| 366 | Tallahassee, FL | 43.3% |
| 367 | Albuquerque, NM | 43.3% |
| 368 | Albany-Schenectady-Troy, NY | 43.0% |
| 369 | Brownsville-Harlingen, TX | 42.9% |
| 370 | San Francisco-Oakland-Hayward, CA | 42.8% |
| 371 | Bridgeport-Stamford-Norwalk, CT | 42.6% |
| 372 | Sierra Vista-Douglas, AZ | 42.6% |
| 373 | Boston-Cambridge-Newton, MA-NH | 42.6% |
| 374 | Boulder, CO | 42.5% |
| 375 | Durham-Chapel Hill, NC | 42.4% |
| 376 | Huntsville, AL | 42.4% |
| 377 | New York-Newark-Jersey City, NY-NJ-PA | 42.2% |
| 378 | Trenton, NJ | 41.0% |
| 379 | San Jose-Sunnyvale-Santa Clara, CA | 40.4% |
| 380 | Washington-Arlington-Alexandria, DC-VA-MD-WV | 39.8% |
| 381 | California-Lexington Park, MD | 39.1% |
| *Note: Averages weighted by occupational employment share* | | |
| *Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data* | | |

**Acknowledgments**

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Endnotes

1. For a thorough summary and discussion of these issues, see Daren Acemoglu and David Autor, “Skills, Tasks and Technologies: Implications for Employment and Earnings.” *Handbook of Labor Economics*, Volume 4b (2001). [↑](#endnote-ref-1)
2. David Autor, Frank Levy, and Richard Murnane “The Skill Content of Recent Technological Change: An Empirical Exploration.” *The Quarterly Journal of Economics (2003)*. [↑](#endnote-ref-2)
3. David Autor, “The ‘task approach’ to labor markets: an overview.” *Journal of Labour Market Research* (2013). [↑](#endnote-ref-3)
4. David Autor notes that there are limits to what is programmable, due to a phenomenon known as Polanyi’s Paradox. Since humans “know more than they know they know” (i.e.know things that are difficult to explain as a matter of codified, programmable steps) there are limits to the substitutability of human taks. See David Autor, “Polanyi’s Paradox and the Shape of Employment Growth.” *Federal Reserve Bank of St. Louis: Economic Policy* (2015). [↑](#endnote-ref-4)
5. Autor, Frey and Osborne, and Mindell have all examined the technical potential and limitations of automation technologies in substituting for human tasks. See, for example, Autor, “Polanyi's Paradox and the Shape of Employment Growth” and “Why Are There Still So Many Jobs? The History and Future of Workplace Automation,” *Journal of Economic Perspectives,* (2015c); Benedikt Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerization” (Oxford: Oxford University, 2013); and David Mindell, *Our Robots, Ourselves: Robotics and the Myths of Autonomy. (*New York: Viking, 2015). About how reduced wages also make labor more competitive vis-a-vis machines, see, for example, Daren Acemoglu and Pascual Restrpo, “The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment.” *American Economic Review* (2017) and Hémous and Olsen, “The Rise of the Machines: Automation, Horizontal Innovation and Income Inequality.” *American Economic Journal: Macroeconomics* (2017). [↑](#endnote-ref-5)
6. Even the most aggressive of mainstream analyses conclude that only moderate shares of the existing job base will be fully automatable in the medium term. Along these lines, Arntz, Gregory, and Zierahn estimate that 9 percent of existing jobs could be fully automatable (based on current task content), and Manyika and others estimate that fewer than 1 percent of existing jobs could be fully automatable (also based on current task content). See Melanie Arntz, Terry Gregory, and Ulrich Zierahn, “The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis,” *Organization Economic Co-operation and Development Social, Employment and Migration Working Papers,* (2016) and James Manyika and others, “A Future That Works: Automation, Employment, and Productivity.” (San Francisco: McKinsey Global Institute, 2017). Note also that Bessen (2015), found that of the 270 occupations in the 1950 Census, 232 of them (or 86 percent) still exist today. Thirty-seven of them went away because either demand fell for those industries or because of technological obsolescence. The demise of just one occupation can be said to have been the result of automation—elevator operators. See James Bessen, *Learning by Doing: The Real Connection between Innovation, Wages, and Wealth. (New Haven,* Yale University Press, 2015). [↑](#endnote-ref-6)
7. For tangible examples of this effect, see Bessen (2015, 2016, 2017a, 2017b). For sector-level impacts see Autor and Salomons (2017). Full citations are as follows: James Bessen, *Learning by Doing;* James Bessen, “How Computer Automation Affects Occupations: Technology, Jobs, and Skills.” (Boston: Boston University School of Law, 2016); James Bessen, “Automation and Jobs: When Technology Boosts Employment.” (Boston: Boston University School of Law, 2017a); and James Bessen, “Scarce Skills; Not Scarce Jobs.” CAPPF International Conference. (2017b). [↑](#endnote-ref-7)
8. See Bessen, *Learning by Doing* and “Automation and Jobs.” [↑](#endnote-ref-8)
9. See Acemoglu and Restrepo, “The Race Between Man and Machine.” [↑](#endnote-ref-9)
10. Ibid. [↑](#endnote-ref-10)
11. David Autor, “Why Are There Still So Many Jobs? The History and Future of Workplace Automation.” *Journal of Economic Perspectives* (2015b). [↑](#endnote-ref-11)
12. Daron Acemoglu and Pascual Restrepo, “Artificial Intelligence, Automation, and Work” in Ajay Agarwal, Avid Goldberg, and Joshua Gans, eds., *Economics of Artificial Intelligence.* [↑](#endnote-ref-12)
13. See Bessen, *Learning by Doing* and “Automation and Jobs.” [↑](#endnote-ref-13)
14. Ibid. [↑](#endnote-ref-14)
15. Ibid. [↑](#endnote-ref-15)
16. Autor (2015b) notes that demand for manual task-intensive services does not appear to be terribly responsive to price changes (demand doesn’t change much with price) but does appear to be responsive to income changes (demand increases as society gets richer). See David Autor. “Why Are There Still So Many Jobs? The History and Future of Workplace Automation.” *Journal of Economic Perspectives* (2015b). See also William Baumol, “Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis.” *American Economic Review* (1967) and David Autor and David Dorn, “The Growth of Low-Skill Service Jobs and the Polarization of the U.S Labor Market.” *American Economic Review* (2013). [↑](#endnote-ref-16)
17. See Autor and Dorn (2013) and Autor (2015b). [↑](#endnote-ref-17)
18. See <https://occupationalinfo.org/> [↑](#endnote-ref-18)
19. James Manyika and others, “A Future that Works: Automation, Employment, and Productivity.” (San Francisco: McKinsey Global Institute, 2017). [↑](#endnote-ref-19)
20. EMSI utilizes government data from the Bureau of Labor Statistics and Census Bureau, and makes certain enhancements for the level of geographic, occupational, and industry detail required for this work. [↑](#endnote-ref-20)
21. Note that EMSI’s data go back only to 2001 though our industry data begin in 2000. The EMSI data are used primarily for adjusting industry occupational employment composition across geographies. In that regard, we assume that occupational structure in 2000 is the same as in 2001. [↑](#endnote-ref-21)
22. See Morgan Frank and others, “Small cities face greater impacts from automation.” *Journal of the Royal Society Interface* (2018); Molly Kinder, “Automation Potential for Jobs in Indianapolis.” New America (2018); and <http://www.governing.com/gov-data/economy-finance/job-automation-metro-area-estimates.html>. [↑](#endnote-ref-22)
23. See Autor and Dorn; Frey and Osborne; Daron Acemoglu and Pascual Restrepo, “Robots and Jobs: Evidence from U.S. Labor Markets.” NBER Working Paper no. 23285. 2017; Frank and others; Manyika and others, “A Future That Works; Kinder; and National League of Cities, “Assessing the Future of Our Work.” (Washington: 2018). [↑](#endnote-ref-23)
24. See Alexandra Spitz-Oener, “Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure,” *Journal of Labor Economics*. [↑](#endnote-ref-24)
25. See Acemoglu and Restrepo, “The Race Between Man and Machine.” [↑](#endnote-ref-25)
26. Frey and Osborne’s (2013) original paper makes use of a 70 percent cutoff for identifying high risk occupations and others have followed their lead. See also Arntz and others “The Risk of Automation for Jobs in OECD Countries,” Richard Berriman and John Hawksworth, “Will robots steal our jobs? The potential impact of automation on the UK and other major economies,” UK Economic Outlook, March 2017 (London: PricewaterhouseCoopers, 2017), Hasan Bakhshi and Phillipe Schneider, “The Future of Skills: Employment in 2030,” (London: NESTA, 2017), Ljubica Nedelkoska and Glenda Quintini, “Automation, skills use and training,” *Organization Economic Co-operation and Development Social, Employment and Migration Working Papers*, (Paris: OECD, 2018). [↑](#endnote-ref-26)
27. The job-creation statistics comes from national Current Employment Statistics data that counts jobs, not workers. For background on the pace and extent of “digitalization” see Mark Muro and others, “Digitalization and the American Workforce” (Washington: Brookings Institution, 2017). [↑](#endnote-ref-27)
28. See David Autor and David Dorn, “The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market.” *American Economic* Review: 103 (5): 1553–1597; and David Autor, "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives* 29(3): 3-30 (2015b). [↑](#endnote-ref-28)
29. See Marten Goos and Alan Manning. “McJobs and MacJobs: The Growing Polarisation of Jobs in the UK,” The Labour Market Under New Labour (London: Palgrave Macmillan, 2003). See also Maarten Goos and Alan Manning, “Lousy and Lovely Jobs: The Rising Polarization of Work in Britain,” *The Review of Economics and Statistics* 89 (1) (MIT Press: Cambridge, 2007) and Maarten Goos, Alan Manning, and Anna Salomons, “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring.” *American Economic Review* Vol 104 (8) (2014). [↑](#endnote-ref-29)
30. Routine-intensive occupations, by virtue of the relative ease with which tasks can be codeified and disaggregated, have also been the easiest to offhshore. As global markets become more integrated in the last three decades, it was these jobs in particular that were most at risk for relocation overseas. See Frank Levy and Richard J. Murnane, *The New Division of Labor: How Computers are Creating the Next Job Market* (Princeton, NJ: Princeton University Press, 2005). [↑](#endnote-ref-30)
31. Bessen (2016) finds the correlation between computer adoption and the share of routine jobs in an industry weaking over the last two decades, leading him to suggest that while initially computerization may have targeted routine-intensive jobs, “subsequent innovations may have targeted more valuable opportunities in occupations that perform abstract tasks” (p. 21). [↑](#endnote-ref-31)
32. We ran a nonlinear least-squares estimation of the exponential function

    Manufacturing employment share in 1980 = b0 \*b1(Routine employment share in 1980)

    The regression yielded an estimate of 707.85 for b0 and 0.033 for b1, both of which were highly significant (p < 0.01, R2 = 0.867). [↑](#endnote-ref-32)
33. Muro and others, “Digitalization and the American Workforce” [↑](#endnote-ref-33)
34. See, for example, Carl Benedikt Frey and Michael Osborne “The Future of Employment: How Susceptible Are Jobs to Computerisation,” Oxford University Martin School (2013); Autor, “Polanyi’s Paradox and the Shape of Employment Growth;” Autor, "Why Are There Still So Many Jobs;” David Mindell, *Our Robots, Ourselves: Robotics and the Myths of Autonom*y (New York, New York: Viking, 2015); and Bakhshi and Schneider, “The Future of Skills: Employment in 2030.” [↑](#endnote-ref-34)
35. We follow Frey and Osborne (2013) and many others in their use of this bracketing to categorize occupations as having low, medium, or high automation potential, although, as we note in the Methodology section of this paper, there remains more work to be done in developing a more rigorous approach to determining what in fact constitutes a “high” level of task-level potential exposure. Note, however, that a fresh statistical check of the data employed here locates a distinct “break” in the automatability figures just above 70 percent, adding some empirical support to the high-end threshold. [↑](#endnote-ref-35)
36. Most notably, in-progress research by Michael Webb suggests the possibility that workers in more numerous abstract task-intensive jobs—which also pay more—may also see heightened levels of task automation as more “non-routine” jobs are exposed to artificial intelligence. See Michael Webb, “What Can Artificial Intelligence Do?” Unpublished manuscript (2018). [↑](#endnote-ref-36)
37. David Autor and Anna Salomons. 2017. “Does Productivity Growth Threaten Employment?” Working paper. [↑](#endnote-ref-37)
38. See Ross Devol “Perspectives on Definining the American Heartland,” (Bentonville, AR: Walton Family Foundation, 2018). [↑](#endnote-ref-38)
39. Muro and others, “Digitalization and the American Workforce” [↑](#endnote-ref-39)
40. Jed Kolko, now the chief economist at Indeed, provided early city-by-city estimates of automation exposure in a look at Republican- and Democratic-leaning counties. See Jed Kolko, “Republican-Leaning Counties Are at Greater Risk of Automation.” *538.* February 17. 2016*.* [↑](#endnote-ref-40)
41. For a powerful investigation of how educational attainment helps people and cities adapt to economic shocks see Edward Glaeser and Albert Saiz, “The Rise of the Skilled City.” Brookings-Wharton Papers on Urban Affairs 5 (2004): 47-94. [↑](#endnote-ref-41)
42. See, for example, Jared Bernstein, “The Importance of Strong Labor Demand” (Washington: The Hamilton Project, 2018); Josh Bivins, “Recommendations for Creating Jobs and Economic Security in the U.S.” (Washington: Economic Policy Institute, 2018); and Robert Atkinson, “Technological Innovation, Employment, and Workforce Adjustment Policies” (Washington: Information Technology and Innovation Foundation, 2018). [↑](#endnote-ref-42)
43. See, for example, Dean Baker and Jared Bernstein, *Getting Back to Full Employment: A Better Bargain to Full Employment.* (Washington: Center for Economic and Policy Research, 2013). [↑](#endnote-ref-43)
44. See Atkinson, “Technological Innovation, Employment, and Workforce Adjustment Policies;” Dean Baker, Sarah Rawlins, and David Stein, “The Full Employment Mandate of the Federal Reserve: Its Origins and Importance,” (Washington: Center for Economic and Policy Research, 2017); Josh Bivens, “The Federal Reserve, Full Employment, and Financial Stability,” *Working Economics Blog*, Economic Policy Institute, May 28, 2014; Thomas Palley, “The Federal Reserve and Shared Prosperity: Why Working Families Need a Fed that Works for Them,” (Washington: Economic Policy Institute, 2015); and Baker and Bernstein, *Getting Back to Full Employment*. [↑](#endnote-ref-44)
45. Atkinson, “Technological Innovation, Employment, and Workforce Adjustment Policies.” [↑](#endnote-ref-45)
46. Bivins, “Recommendations for Creating Jobs and Economic Security in the U.S.” [↑](#endnote-ref-46)
47. Daron Acemoglu and Pascual Restrepo, “Artificial Intelligence, Automation, and Work.” [↑](#endnote-ref-47)
48. See Mark Muro and others, “America’s Advanced Industries: What They Are, Where They Are, and Why They Matter.” (Washington: Brookings Institution, 2015) and Mark Muro and others, “Digitalization and the American Workforce” (Washington: Brookings Institution, 2017). [↑](#endnote-ref-48)
49. China’s 2017 ”Next Generation AI Development Plan” describes AI as a “strategic technology” that has become “a focus of international competition.” According to the document, China will “firmly seize the strategic initiative” and reach “world leading levels” of AI investment by 2030, with over $150 billion in government funding.” See China State Council, “A Next Generation AI Development Plan.” Among the concerns Americans should have about ceding AI leadership to China are: weak Chinese ethics and safety histories; Chinese “data protectionism;” and the use of AI to further autocracy, as through “predictive policing,” high-tech surveillance, and state-of-the-art censorship. See, for example, “Why China’s AI push is worrying.” *The Economist.* July 27th, 2017 and Christina Larson, “China’s massive investment in artificial intelligence has an insidious downside.” *Science.* February 8, 2018. [↑](#endnote-ref-49)
50. For solid overviews of existing and needed research priorities on defense and civilian automation, robotics, and artificial intelligence see, among others, John Sargent, “Federal Research and Development Funding (R&D): FY2019.” (Washington : Congressional Research Service, 2018); National Science and Technology Council, “The National Artificial Intelligence Research and Development Strategic Plan.” (Washington: 2016); Executive Office of the President, “Preparing for the Future of Artificial Intelligence.” (Washington: National Science and Technology Council, 2016); Govini, “Artificial Intelligence, Big Data, and Cloud Taxonomy” (Washington: 2018); and Daniel Hoadley and Nathan Lewis, “Artificial Intelligence and National Security,” (Washington: Congressional Research Service, 2018). [↑](#endnote-ref-50)
51. See National Science and Technology Council, “The National Artificial Intelligence Research and Development Strategic Plan.” [↑](#endnote-ref-51)
52. See <https://vectorinstitute.ai/about/#visionmission>. [↑](#endnote-ref-52)
53. Mandy Kovacs, “Toronto’s Vector Institute expands its AI mission as it finishes assembling team,” *IT World Canada*, December 11, 2017. [↑](#endnote-ref-53)
54. Ibid. [↑](#endnote-ref-54)
55. See <https://www.cifar.ca/ai/pan-canadian-artificial-intelligence-strategy>. [↑](#endnote-ref-55)
56. See Jozef Konings and Stijn Vanormelingen, “The Impact of Training on Productivity and Wages: Firm-Level Evidence,” *Review of Economics and Statistics* 97 (2) (2015): 485-497; see also Gérard Ballot, Fathi Fakhfakh, and Erol Taymaz, “Who benefits from training and R&D, the firm or the workers?” *British Journal of Industrial Relations* 44(3): 473-495; and Daron Acemoglu and Jörn-Steffen Pischke, “Beyond Becker: Training in Imperfect Labor Markets,” *The Economic Journal* 109 (February) (1999): F112-F142. [↑](#endnote-ref-56)
57. See Konings and Vanormelingen, “The Impact of Training on Productivity and Wages;” Ballot, Fakhfakh, and Taymaz, “Who benefits from training and R&D, the firm or the workers?”; and Acemoglu and Pischke, “Beyond Becker.” [↑](#endnote-ref-57)
58. “Economic Report of the President Together with the Annual Report of the Council of Economic Advisers,” (Council of Economic Advisers, 2015). [↑](#endnote-ref-58)
59. See National Skills Coalition, “The Business Case for Upskilling: How Companies Benefit when Service Workers Improve their Skills”; see also Kausik Rajgopal and Steve Westly, “How Tech Companies Can Help Upskill the U.S. Workforce,” *Harvard Business Review*, February 20, 2018. [↑](#endnote-ref-59)
60. Muro and others, “Digitalization and the American Workforce”; see also Robert D. Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change” (Washington: Information Technology and Innovation Foundation, 2018). [↑](#endnote-ref-60)
61. For example, Oregon, in partnership with for-profit coding school Treehouse and the non-profit Worksystems Inc., developed an initiative known as Code Oregon, which provided free coding training to over 11,000 Portland-area residents from 2014 to 2016, see <http://codeoregon.org/PDFs/Code_Oregon_%201.0_Transition_%202016-02-25.pdf>. Existing educational institutions are also pioneering affordable accelerated learning. For example, City College of Chicago is piloting free accelerated learning programs in both cybersecurity and iOS development, in partnership with the Department of Defense and Apple, respectively, see Andreas Rekdal, “Community colleges launch free coding bootcamps to fill Chicago’s talent pipeline,” *Built in Chicago*, February 26, 2018. [↑](#endnote-ref-61)
62. As an example of ongoing federal efforts, in 2016 the Obama Administration pioneered the Educational Quality through Innovative Partnerships (EQUIP) program, a pilot program at the Department of Education evaluating federally-funded partnerships between colleges and non-traditional education providers. The eight pilots, which participating individuals were able to pay for using federal student aid dollars, include partnerships with coding schools such as The Flatiron School, online course providers such as Study.com, and major U.S. employers such as GE. The federal government should ensure that the results of this pilot program are rigorously assessed, and help scale up models that are shown to be effective. For more information, see: <https://tech.ed.gov/equip/> [↑](#endnote-ref-62)
63. Interview with Jeffrey Mazur; see also <https://www.launchcode.org> [↑](#endnote-ref-63)
64. See <https://generalassemb.ly/corporate-digital-training> [↑](#endnote-ref-64)
65. See Muro and others, “Digitalization and the American Workforce”; see also Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change.” As an illustrative example, Colorado has pioneered this effort through its partnership with the Markle Foundation’s Skillful initiative, and governors in 20 states are now partnering to implement this approach more broadly across the U.S., see <https://www.markle.org/rework-america/skillful> and <https://www.markle.org/about-markle/media-release/skillful-state-network>; see also Steve Lohr, “A New Kind of Tech Job Emphasizes Skills, Not a College Degree,” The New York Times, June 28, 2017. [↑](#endnote-ref-65)
66. See Edward Alden and others, “The Work Ahead: Machines, Skills, and U.S. Leadership in the Twenty-First Century” (Washington: Council on Foreign Relations, 2018). [↑](#endnote-ref-66)
67. See Ballot, Fakhfakh, and Taymaz, “Who benefits from training and R&D, the firm or the workers?; see also Acemoglu and Pischke, “Beyond Becker.” [↑](#endnote-ref-67)
68. Alastair Fitzpayne and Ethan Pollack, “Worker Training Tax Credit: Promoting Employer Investments in the Workforce” (Washington: The Aspen Institute, 2017). [↑](#endnote-ref-68)
69. Ibid. [↑](#endnote-ref-69)
70. Lifelong learning accounts have been piloted in Maine and Washington State. In Maine’s pilot, 40 percent of contributions were made by employees, another 38 percent came from employers, and 22 percent from state matching grants and other outside sources. See "Lifelong Learning Accounts: Working Together for a Better Future" (Maine Department of Labor and Maine Bureau of Employment Services, 2009). [↑](#endnote-ref-70)
71. For an example of direct government contributions to lifelong learning accounts, as part of its SkillsFuture program, the government of Singapore provides all Singaporeans aged 25 and older a credit of S$500 (U.S. $360), which is topped up at regular intervals. The credit remains in the individual’s SkillsFuture Credit account for life, so they can use them at any time to pay for education or training of their choice. See: <http://www.skillsfuture.sg/Credit> [↑](#endnote-ref-71)
72. See Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change”; see also Alden and others, “The Work Ahead.” [↑](#endnote-ref-72)
73. Muro and others, “Digitalization and the American Workforce.” [↑](#endnote-ref-73)
74. Ibid. [↑](#endnote-ref-74)
75. According to the market analytics firm Burning Glass, liberal arts students with technical skills, such as data analysis or computer programming, can double the number of jobs available upon graduation, as well as earn a salary premium of $6,000 over students without those skills, see Burning Glass, “The Art of Employment: How Liberal Arts Graduates can Improve their Labor Market Prospects” (2013). [↑](#endnote-ref-75)
76. See Claire Cain Miller, “Making Computer Science More Inviting: A Look at What Works,” *The New York Times*, May 21, 2015. [↑](#endnote-ref-76)
77. For additional discussion on expanding tech minors, certification, and other relevant learning experiences see: PriceWaterhouseCoopers and the Business-Higher Education Forum, “Investing in America’s data science and analytics talent: The case for action” (2017); Mark Schneider and Matthew Sigelman, “Saving the Liberal Arts: Making the Bachelor’s Degree a Better Path To Labor Market Success” (Washington: American Enterprise Institute and Burning Glass, 2018); Burning Glass, “How to Double Job Opportunities for Biology & Psychology Majors” (2016); and Scott Bittle, “Don’t Forget the Spreadsheet: Picking Up Job Skills That Pay Off in the Labor Market,” Burning Glass blog, April 19, 2016. [↑](#endnote-ref-77)
78. The Economy League of Greater Philadelphia, “Driving Tech Talent Growth in PHL - Technical Report” (2017); see also Felix W. Ortiz III, “Why Tech Companies and Community Colleges Should Form Deeper Partnerships,” *Huffington Post*, April 14, 2015; and Sheila Edwards Lange, “Look to community colleges for diverse tech-industry talent,” *The Seattle Times*, December 7, 2017. [↑](#endnote-ref-78)
79. See Code.org footnote: <https://docs.google.com/document/d/1gySkItxiJn_vwb8HIIKNXqen184mRtzDX12cux0ZgZk/pub#h.khy2cje7n74>. Some states—including Arkansas, West Virginia, and Virginia—are embarking on urgent efforts to expand equitable CS education, including by implementing many of the policies recommended by the non-profit Code.org and its partners, such as requiring CS instruction at K-12 schools and counting computer science as a graduation requirement, see Jim Stanton and others, “State of the States Landscape Report: State-Level Policies Supporting Equitable K–12 Computer Science Education” (Boston: Education Development Center, Inc., 2017). [↑](#endnote-ref-79)
80. David Kosbie, Andrew W. Moore, and Mark Stehlik, “How to Prepare the Next Generation for Jobs in the AI Economy,” *Harvard Business Review*, June 5, 2017. [↑](#endnote-ref-80)
81. See Alison DeNisco Rayome, “The state of women in computer science: An investigative report,” *Tech Republic*, September 29, 2017; see also <https://datausa.io/profile/cip/110701/#demographics>, access July 2, 2018. [↑](#endnote-ref-81)
82. Muro and others, “Digitalization and the American Workforce.” [↑](#endnote-ref-82)
83. Miller, “Making Computer Science More Inviting.” [↑](#endnote-ref-83)
84. Auon, *Robot-Proof*. [↑](#endnote-ref-84)
85. Ibid. [↑](#endnote-ref-85)
86. See Mona Mourshed and others, “Education to Employment: Designing a System that Works” (Washington: McKinsey Center for Government, 2013); see also Auon, *Robot-Proof*. [↑](#endnote-ref-86)
87. See Iram Siraj, “Teaching kids 21st century skills early will help prepare them for their future,” *The Conversation*, November 13, 2017, an edited extract from Iram Siraj, “Nurturing ‘21st Century Skills’ in Early Childhood Education and Care.” In Leslie Loble, Tish Creenaune, and Jackie Hayes, ed. *Future Frontiers: Education for an AI World* (Melbourne: Melbourne University Press, 2017). [↑](#endnote-ref-87)
88. Heather Long, “By age 3, inequality is clear: Rich kids attend school. Poor kids stay with a grandparent,” *The Washington Post*, September 26, 2017; see also: “Preschool and Kindergarten Enrollment,” <https://nces.ed.gov/programs/coe/indicator_cfa.asp>, accessed May 11, 2018. For information on variations in state-by-state enrollment and funding, as well as disparities in access to early childhood education by race, see: “A Matter of Equity: Preschool in America” (Department of Education, 2015); Rutgers Graduate School of Education, “The State of Preschool 2017: State Preschool Yearbook” (2018); and Claudio Sanchez and Elissa Nadworny, “Preschool, A State-By-State Update,” *National Public Radio*, May 24, 2017. [↑](#endnote-ref-88)
89. Andrew McAfree and Erik Brynjolfsson, *Machine Platform Crowd: Harnessing Our Digital Future* (New York: W.W. Norton, 2017). [↑](#endnote-ref-89)
90. For background on evidence that “soft” or “noncognititive” skills like social awareness or leadership skills—as opposed to cognitive skills like math or reading that are measured by standardized tests—strongly improve labor market outcomes see, Diane Whitmore Schanzanbach and others, “Seven Facts on Noncognititive Skills from Education to the Labor Market” (Washington: Hamilton Project, 2016). [↑](#endnote-ref-90)
91. See James Walker, “Adaptability in the Workplace: An Exploratory Study on Adaptive Performance in the Workplace Using a Scenario-Based Tool.” Dissertation. University of Pennsylvania, 2015 and Manuel London, “Lifelong Learning: Introduction and the Committee on Information Technology, Automation, and the U.S. Workforce.” [↑](#endnote-ref-91)
92. In the business school realm Ed Hess writes that: “What is needed is a new definition of being smart, one that promotes higher levels of human thinking and emotional engagement. The New smart will be determined not by what or how you know but by the quality of your thinking, listening, relating, collaborating, and learning.” See Ed Hess, “In the AI Age, `Being Smart’ Will Mean Something Completely Different.” (Boston: *Harvard Business Review*, 2017). On the development if teams’ emotional intelligence through design thinking see Brian Romer, “How the Practice of Design Enhances Artificial Intelligence” (Boston: Thompson Reuters Labs, 2018). And for background on recent thinking on “human skills” in education see Paul Tough, *How Children Succeed* (Boston: Mariner, 2012) and Paul Tough, *Helping Children Succeed: What Works and Why* (Boston: Houghton Mifflin, 2016). [↑](#endnote-ref-92)
93. Daron Acemoglu and Pascual Restrepo, “Artificial Intelligence, Automation and Work” NBER Working Paper No. 24196. [↑](#endnote-ref-93)
94. Edward Alden, *Failure to Adjust: How Americans Got Left Behind in the Global Economy* (Lanham, Md.: Roman & Littlefield, 2017). [↑](#endnote-ref-94)
95. For the official Bureau of Labor Statistics definition of displaced workers, see: <https://www.bls.gov/news.release/disp.tn.htm> [↑](#endnote-ref-95)
96. WIOA’s dislocated workers program does not have an eligibility requirement related to cause of dislocation. However, workers must meet the following requirements in order to receive benefits under this program:

    Has been terminated or laid off, or has been notified of a termination or layoff;

    Is sufficiently attached to the workforce, demonstrated with through eligibility for/exhaustion of unemployment compensation or through other means; and

    Is unlikely to return to their previous industry or occupation

    There is also flexibility in applying these criteria, e.g. in the case of an anticipated facility closing or for self-employed workers. Workers who do not meet these three criteria may be eligible to receive many of the same services as part of the WIOA Adult program. For more information, see: David H. Bradley, “The Workforce Innovation and Opportunity Act and the One-Stop Delivery System” (Congressional Research Service, 2015). [↑](#endnote-ref-96)
97. According to the U.S. Bureau of Labor Statistics, from 2013–2015 (the most recent period that reporting is available) there were 7.4 million workers displaced in the U.S. economy. However, during that time, the WIOA Displaced Workers Program served fewer than 2 million participants, and only 3.7 million participants received support beyond self-service resources from the WIOA Adult program. Furthermore, both of these numbers are likely to double-count individual workers across years and programs. For more information on the number of displaced workers in the U.S. economy, see: <https://www.bls.gov/news.release/archives/disp_08252016.pdf>; for more information on access to WIOA programs, see: <https://www.doleta.gov/performance/results/WIASRD_state_data_archive.cfm>. [↑](#endnote-ref-97)
98. See Mark Muro and Joseph Parilla, “Maladjusted: It’s time to reimagine economic ‘adjustment’ programs,” *The Avenue*, January 10, 2017. [↑](#endnote-ref-98)
99. President Clinton proposed several workforce development reform bills, including the Reemployment Act of 1994, which called for a single, universal displaced worker assistance program including income support. For more on that program see: <https://aging.ny.gov/ProvidersandStaff/Issuances/Archives/1994/IM/94-IM-40-Proposed-Reemployment-Act-of-1994.pdf> and <https://www.congress.gov/bill/103rd-congress/house-bill/4050>. President Obama proposed a Universal Displaced Worker program as part of his FY 2013 budget proposal. Information on the Obama Administration’s Universal Displaced Worker program can be found here: <https://obamawhitehouse.archives.gov/the-press-office/2012/03/12/white-house-announces-details-president-s-plan-provide-americans-job-tra>. [↑](#endnote-ref-99)
100. “Active Labor Market Policies: Theory and Evidence for What Works” (Council of Economic Advisers, 2016); see also: “Artificial Intelligence, Automation, and the Economy,” (Executive Office of the President, 2016); see also Marios Michaelides and others, “Impact of the Reemployment and Eligibility Assessment (REA) Initiative in Nevada” (Columbia, Md.: IMPAQ International, 2012). [↑](#endnote-ref-100)
101. See Alden and others, “The Work Ahead” and Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change.” [↑](#endnote-ref-101)
102. This includes 883,920 exiters from the WIOA Adult program, 81 percent of whom were either not employed or had received a layoff notice, and 426,001 participants in the WIOA Dislocated Worker program, 93 percent of whom were either not employed or had received a layoff notice. Only 11 percent of workers in the Adult program, and only 14 percent of workers in the Dislocated Worker program received training services. Note: some workers received services from both programs. See: Social Policy Research Associates, “PY 2015 WIOA Trends Over Time” (2016). [↑](#endnote-ref-102)
103. This is applicable for both FY 2015 and FY 2016, the two most recent years with data available, see “Trade Adjustment Assistance for Workers Program: Fiscal Year 2015” (U.S. Department of Labor, 2015).; see also “Trade Adjustment Assistance for Workers Program: Fiscal Year 2016” (U.S. Department of Labor, 2016). [↑](#endnote-ref-103)
104. Selingo, “The False Promises of Worker Retraining.” [↑](#endnote-ref-104)
105. Ibid.; see also: Chana Joffe-Walt, “Unfit for Work: The startling rise of disability in America,” *National Public Radio*, 2013. [↑](#endnote-ref-105)
106. Selingo, “The False Promises of Worker Retraining”; see also Lawrence F. Katz, “Discussion of Alan Krueger’s “Where Have All the Workers Gone?”” (Washington: Brookings Institution, 2017). [↑](#endnote-ref-106)
107. Selingo, “The False Promises of Worker Retraining”; see also Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change.” [↑](#endnote-ref-107)
108. Louis S. Jacobson, Robert J. LaLonde, and Daniel G. Sullivan, “Policies to Reduce High-Tenured Displaced Workers’ Earnings Losses Through Retraining” (Washington: The Hamilton Project, 2011). [↑](#endnote-ref-108)
109. See: <http://www.oecd.org/employment/activation.htm>; see also Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change.” [↑](#endnote-ref-109)
110. Chad Stone and William Chen, “Introduction to Unemployment Insurance” (Washington: Center on Budget and Policy Priorities, 2014); see also: <https://oui.doleta.gov/unemploy/ui_replacement_rates.asp> [↑](#endnote-ref-110)
111. See “Comparison of State Unemployment Laws 2018: Monetary Entitlement” (Department of Labor, 2018); see also: Center for Budget and Policy Priorities, “Policy Basics: How Many Weeks of Unemployment Compensation Are Available?” (2018). And while there is a federal Extended Benefits program that lengthens the amount of time that workers can receive income support, it is only available during times of high unemployment or a rapid increase in unemployment. As a result, workers displaced when the unemployment rate is lower cannot access it; see Julie M. Whittaker and Katelin P. Isaacs, “Unemployment Insurance: Programs and Benefits” (Congressional Research Service, 2016). [↑](#endnote-ref-111)
112. Atkinson, “How to Reform Worker-Training and Adjustment Policies for an Era of Technological Change.” [↑](#endnote-ref-112)
113. Nordic Council of Ministers, “Labour Market Mobility in Nordic Welfare States” (2010). [↑](#endnote-ref-113)
114. Catherine Stephan, “Ins-and-outs of the Danish flexicurity model” (Paris: BNP Paribas, 2017). [↑](#endnote-ref-114)
115. Salmon, “The Future of Work in New Zealand: Education and Training – Lessons from Denmark.” [↑](#endnote-ref-115)
116. Nordic Council of Ministers, “Labour Market Mobility.” [↑](#endnote-ref-116)
117. Jan Hendeliowitz, “Danish Employment Policy National Target Setting, Regional Performance Management and Local Delivery” (Copenhagen: Danish National Labour Market Authority, 2008). [↑](#endnote-ref-117)
118. Eurostat via the Google Public Data portal, accessed April 17, 2018. [↑](#endnote-ref-118)
119. <https://data.oecd.org/emp/employment-rate.htm>, accessed April 17, 2018. [↑](#endnote-ref-119)
120. See “GDP per hour worked,” OECD <https://data.oecd.org/lprdty/gdp-per-hour-worked.htm> [↑](#endnote-ref-120)
121. See <http://thegedi.org/global-entrepreneurship-and-development-index/> [↑](#endnote-ref-121)
122. For discussions around the relationship between flexicurity and worker risk-taking in Denmark, see Thomas Bredgaard and Flemming Larsen, “Comparing Flexicurity in Denmark and Japan,” (Aalborg, Denmark: Centre for Labour Market Research at Aalborg University, 2018); Thomas Bredgaard and Arthur Daemmrich, “The Welfare State as an Investment Strategy: Denmark’s Flexicurity Policies,” in Ashok Bardhan, Dwight Jaffee, and Cynthia Kroll, ed. *The Oxford Handbook of Offshoring and Global Employment* (Oxford: Oxford University Press, 2013); Daemmrich, Arthur A., and Benjamin Kramarz. "Denmark: Globalization and the Welfare State" (Cambridge: Harvard Business School, 2009, revised 2012); and Thomas Bredgaard, Flemming Larsen, and Per Kongshøj Madsen, “Opportunities and challenges for flexicurity – The Danish example,” *Transfer: European Review of Labour and Research*, 12 (1) (2006): 61–82. [↑](#endnote-ref-122)
123. Geoff Williams, “The Hidden Costs of Moving,” *U.S. News and World Report*, April 30, 2014. [↑](#endnote-ref-123)
124. Alden and others, “The Work Ahead”; see also Mihir Desai, “Move Americans to Jobs, Not the Other Way Around,” Bloomberg View, August 28, 2017. [↑](#endnote-ref-124)
125. See Indivar Dutta-Gupta and others, “Lessons Learned from 40 Years of Subsidized Employment Programs” (Washington: Georgetown Law Center on Poverty and Inequality, 2016); see also Rachel West, Rebecca Vallas, and Melissa Boteach, “A Subsidized Jobs Program for the 21st Century” (Washington: Center for American Progress, 2015). [↑](#endnote-ref-125)
126. For information on the WOTC, see <https://www.doleta.gov/business/incentives/opptax/>; see also Elizabeth Lower-Basch, “Rethinking Work Opportunity: From Tax Credits to Subsidized Job Placements” (Washington: Center for Law and Social Policy, 2011). [↑](#endnote-ref-126)
127. See Lower-Basch, “Rethinking Work Opportunity,” and Dutta-Gupta and others, “Lessons Learned from 40 Years of Subsidized Employment Programs.” [↑](#endnote-ref-127)
128. “Policy Basics: The Earned Income Tax Credit,” (Washington: Center on Budget and Policy Priorities, 2018). [↑](#endnote-ref-128)
129. Congress has proposed several plans to expand the EITC in recent years, but none have yet passed. One of the most ambitious plans to expand the EITC comes from Rep. Ro Khanna (D-Calif.) and Sen.r Sherrod Brown (D-Ohio). Their proposal incorporates several reforms that will make the EITC more effective as automation pushes a larger portion of the workforce into lower-wage jobs, including increasing the payments provided to workers, including childless workers, as well as raising the maximum income threshold. See Ferenstein, “Wages are stagnating, robots are taking our jobs. This Democrat has a $1.4 trillion solution.” [↑](#endnote-ref-129)
130. The IRS has already developed the infrastructure for making regular tax credit payments through the monthly tax credits it provides to offset medical insurance premiums bought through the Affordable Care Act (ACA) exchanges. This infrastructure could be levied to make similar payments to workers that qualify for the EITC. See: Steve Holt, “Periodic payment of the Earned Income Tax Credit revisited,” (Washington: Brookings Institution, 2015); see also: Alan Berube, “Want to help the working class? Pay the EITC differently,” *The Avenue*, June 28, 2017. [↑](#endnote-ref-130)
131. See <https://www.bls.gov/news.release/disp.t07.htm> [↑](#endnote-ref-131)
132. See: Benjamin Collins, “Trade Adjustment Assistance for Workers and the TAA Reauthorization Act of 2015” (Congressional Research Service, 2016). [↑](#endnote-ref-132)
133. See Rob Valletta, “Involuntary Part-Time Work: Yes, It’s Here to Stay,” SF Fed Blog, April 11, 2018; see also Martha Gimbel, “October Jobs Report Preview: Many of Today’s Part-Time Workers Are Hoping to Find Full-Time Jobs,” Indeed Hiring Lab *State of the Labor Market*, October 29, 2018. [↑](#endnote-ref-133)
134. Andrew Stettner, Michael Cassidy And George Wentworth, “A New Safety Net for An Era of Unstable Earnings” (Washington: The Century Foundation, 2016). [↑](#endnote-ref-134)
135. Mark Muro and Clara Hendrickson, “Gouging the Safety Net is Especially Untimely Now.” *The Avenue,* December 20, 2017. [↑](#endnote-ref-135)
136. See: J. Mark Iwry and David C. John, “Pursuing Universal Retirement Security Through Automatic IRAs” (Washington: Brookings Institution, 2009); see also David C. John, “Automatic IRA Builds Retirement Security” (Washington: The Heritage Foundation, 2010) and David C. John, “The Automatic IRA: A Conservative Way to Build Retirement Security,” *The Daily Signal*, August 13, 2010. [↑](#endnote-ref-136)
137. Mark Muro, “Failure to adjust: The case of the auto-IRA,” *The Avenue*, May 8, 2017. [↑](#endnote-ref-137)
138. Robert Steyer, “Oregon treasurer, in from the start, follows through on auto-IRA plan,” *Pensions & Investments Online*, October 29, 2018. [↑](#endnote-ref-138)
139. Ibid.; see also Pew Charitable Trusts, “Early Participation Levels for Oregon Retirement Savings Program Indicate Promising Start,” March 13, 2018. [↑](#endnote-ref-139)
140. See “2018 Survey of Oregonians: OregonSaves Program,” <https://www.aarp.org/research/topics/economics/info-2018/oregon-retirement-savings.html> [↑](#endnote-ref-140)
141. See Bureau of Labor Statistics Employee Benefits Survey, <https://www.bls.gov/ncs/ebs/#data>. The federal Family and Medical Leave Act (FMLA) does not guarantee paid leave, merely 12 weeks of unpaid leave for workers. However, because FMLA only applies to companies with 50 or more employees, many workers in the service industry, which has many small businesses, do not even get those protections. Paid family leave has been a stated priority of the Trump Administration, but federal efforts to date have stalled. However, five states and Washington, DC have paid family leave policies. Meanwhile, an additional nine states and over 30 municipalities have enacted paid sick leave. See <http://www.ncsl.org/research/labor-and-employment/paid-family-leave-resources.aspx> and <https://www.shrm.org/resourcesandtools/legal-and-compliance/state-and-local-updates/pages/paid-sick-leave-laws-by-state.aspx>.

     [↑](#endnote-ref-141)
142. For a review of the U.S. government’s definition of contingent work see <https://www.bls.gov/cps/contingent-and-alternative-arrangements-faqs.htm>; for a broader assessment of contingent work in the economy see: Annette Bernhardt, “Labor Standards and the Reorganization of Work: Gaps in Data and Research” (Berkeley: Institute for Research and Labor Employment, 2014). Despite a variety of recent efforts, it is difficult to quantify the exact size of the contingent economy. By some measures, the contingent economy is growing. For example, Census Bureau data shows that “nonemployer firms,” or firms that have no employees and mostly constitute unincorporated self-employed freelancers, have increased by nearly 10 million since 1997. Nonemployer firms are also increasing relative to traditional payroll employment – while in 1997 there were 8.3 payroll workers for every nonemployer firm, by 2016 that ratio had fallen to 6 payroll workers for every nonemployer firm. For more information, see Robert Maxim and Mark Muro, “Rethinking worker benefits for an economy in flux,” The Avenue, March 30, 2018; see also: Ian Hathaway and Mark Muro, “Tracking the gig economy: New Numbers,” The Avenue, October 13, 2016. Other analyses have shown similar trends, including a widely cited study by Lawrence F. Katz and Alan B. Krueger that found alternative work arrangements increased from 10.7 percent of the workforce in 2005 to 15.8 percent in 2015; see Lawrence F. Katz and Alan B. Krueger, “The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015” NBER Working Paper No. 22667. Conversely, the Bureau of Labor Statistics’ 2018 Contingent Worker Survey showed that a smaller proportion of Americans now use alternative work arrangements as their primary source of income, dropping from 10.7 percent of the workforce in 2005, to 10.1 percent in 2017, some 15.5 million workers; see Bureau of Labor Statistics, “Contingent and Alternative Employment Arrangements – May 2017” (Department of Labor, 2018). [↑](#endnote-ref-142)
143. Libby Reder and others, “Portable Benefits Resource Guide” (Washington: The Aspen Institute, 2016). [↑](#endnote-ref-143)
144. See Bridget Ansel, “The pitfalls of just-in-time-scheduling” (Washington: Washington Center for Equitable Growth); and National Partnership for Women and Families, “Schedules That Work” (2017). [↑](#endnote-ref-144)
145. For a more in-depth discussion of the impacts of paycheck uncertainty, see Mark Muro and Clara Hendrickson, “Managing uncertainty: Paycheck volatility demands new responses,” *The Avenue*, March 1, 2018. [↑](#endnote-ref-145)
146. See Joan C. Williams and others, “Stable Scheduling Increases Productivity and Sales: The Stable Scheduling Study” (San Francisco: The Center for WorkLife Law, 2018). [↑](#endnote-ref-146)
147. For a brief overview of the Economic Adjustment Program, see here: <https://www.eda.gov/pdf/about/Economic-Adjustment-Assistance-Program-1-Pager.pdf>; a more comprehensive overview can be found in the Department of Commerce Fiscal Year 2017 Congressional Budget Request: <http://www.osec.doc.gov/bmi/budget/FY17CBJ/EDA%20FY%202017%20Congressional%20Submission%202-8-16%20OMB%20cleared%20508%20Compliant.pdf>. For an overview on the TAA for Firms program, see Rachel F. Fefer, “Trade Adjustment Assistance for Firms” (Congressional Research Service, 2011). Additional information on both programs can be found in their respective annual reports, available here: <https://www.eda.gov/annual-reports/>. [↑](#endnote-ref-147)
148. For an overview of the work of the Appalachian Regional Commission, see: <https://www.arc.gov/about/>; for an overview of work by the Delta Regional Authority, see: <http://dra.gov/about-dra/mission-and-vision/>. [↑](#endnote-ref-148)
149. See Mark Muro, “Economic Cluster Policy Begins to Work,” *The Avenue*, July 9, 2013. [↑](#endnote-ref-149)
150. Assessments of the economic impacts of different regional development programs show that these programs can have a positive impact, but that additional evaluation is needed to determine which types of interventions are the most effective. An assessment by the Upjohn Institute notes that EDA programs tend to have a positive impact on job creation, but evidence around generating positive impacts on income, local tax revenues, reemploying workers, and attracting firms are more mixed; see: Brad R. Watts and others, “What Should EDA Fund? Developing a Model for Pre-Assessment of Economic Development Investments” (Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, 2009). A comprehensive assessment of the Appalachian Regional Commission found that Appalachia had faster income and population growth relative to a control group over its history, see: Andrew Isserman and Terance Rephann, “The Economic Effects of the Appalachian Regional Commission: An Empirical Assessment of 26 Years of Regional Development Planning,” *Journal of the American Planning Association* 61:3 (1995): 345-364. An assessment by the Department of Agriculture’s Economic Research Service found the Delta Regional Authority had positive effects on income in the region, see: John Pender and Richard Reeder, “Per Capita Income Grows Faster in Delta Regional Authority Counties” (Department of Agriculture, 2012). However, a Government Accountability Office (GAO) report found that as a whole, federal economic development programs tend to be duplicative, see: “Efficiency and Effectiveness of Fragmented Economic Development Programs Are Unclear” (Government Accountability Office, 2011). Another GAO report found that the TAA for firms program had positive impacts, but that measurement and data collection could improve, see: “Commerce Program Has Helped Manufacturing and Services Firms, but Measures, Data, and Funding Formula Could Improve” (Government Accountability Office, 2012). [↑](#endnote-ref-150)
151. For discussions on better linking workforce development policies to broader economic development, see: Bipartisan Policy Center, “The Appalachia Initiative: A Bipartisan Approach for the 21st Century” (2017); see also Aspen Institute, “Where Labor Supply Meets Labor Demand: Connecting Workforce Development to Economic Development in Local Labor Markets” (2011). For a more recent discussion on the goals of WIOA in improving linkages between economic development and workforce development, see: Lauren Eyster, “Coordinating Workforce and Economic Development under WIOA” (Washington: Urban Institute, 2015). [↑](#endnote-ref-151)
152. For an example of improving place-based policies for distressed communities, see Bartik, “Bringing Jobs to People: How Federal Policy Can Target Job Creation for Economically Distressed Areas.” Additional assessments exist for improving the impact of place-based strategies, for example, see: Amy Liu and Alan Berube, “Matching Place-Based Strategies to the Scale of the Market,” The Avenue, January 21, 2015; Rolf Pendall and others, “Revitalizing Neighborhoods: The Federal Role” (Washington: Urban Institute, 2016); and Promoting Place-Based Strategies to Address Poverty: Exploring the Governor’s Role” (Washington: National Governor’s Association, 2017). For broader discussions on how to improve economic development programs in the U.S., see: Ann Markusen and Amy Glasmeier, “Overhauling and Revitalizing Federal Economic Development Programs” Economic Development Quarterly 22:2 (2008): 83-91; and: Timothy J. Bartik, “What Works in Economic Development” (Kalamazoo, MI: The Upjohn Institute for Employment Research, 2016). [↑](#endnote-ref-152)
153. Trade Adjustment Assistance included a TAA for Communities program from 1974-1982, and again from 2009-2011. In the most recent iteration, the program provided a variety of grants to trade-impacted communities, including strategic planning grants, as well as grants to community colleges to fill the education and skills gap of workers in those communities. The latter program operated through September 2018. For an overview of the TAA for Communities program as a whole, see Eugene Boyd and Cassandria Dortch, “Trade Adjustment Assistance for Communities: The Law and Its Implementation” (Congressional Research Service, 2011), and Alden, *Failure to Adjust*. For a more detailed assessment of the TAA grants to community colleges, see: <https://doleta.gov/taaccct/>. For information on the Department of Defense’s adjustment programs, operated through the Office of Economic Adjustment, see: <http://www.oea.gov/>. [↑](#endnote-ref-153)
154. See, for example, Benjamin Austin, Edward Glaeser, and Lawrence Summers, “Saving the Heartland: Place-Based Policies in 21st Century America.” (Washington: Brookings Papers on Economic Activity, forthcoming). See also Neil Irwin, “One Country Thrives. The Next One Over Struggles. Economists Take Note,” *The New York Times,* June 29, 2018. For an overview of the spatial distribution of robots in workplaces, see Mark Muro, “Where the robots are,” *The Avenue*, August 14, 2017. [↑](#endnote-ref-154)
155. See <https://cuyahogacounty.us/development/businesses/skillup>; see also Thomas A. Steward and others, “Help Wanted: How Middle Market Companies Can Address Workforce Challenges to Find and Develop the Talent They Need to Grow (Washington: Brookings Instituion, [↑](#endnote-ref-155)
156. See Timothy J. Bartik, “Bringing Jobs to People: How Federal Policy Can Target Job Creation for Economically Distressed Areas” (Washington: The Hamilton Project, 2010). [↑](#endnote-ref-156)
157. See <http://www.skillful.com/policymakers> [↑](#endnote-ref-157)
158. See [www.nist.gov/mep](http://www.nist.gov/mep). For a recent evaluation see Clifford Lipscomb and others, “Evaluating the Long-Term Effect of NIST MEP Services on Establishment Performance.” (Washington: Center for Economic Studies, 2015). [↑](#endnote-ref-158)
159. See <http://arminstitute.org/> and [www.uilabs.org/innovation-platforms/manufacturing/](http://www.uilabs.org/innovation-platforms/manufacturing/). [↑](#endnote-ref-159)
160. For preliminary assessments of the Manufacturing USA institutes see Deloitte, “Manufacturing USA: A Third Party Evaluation of Design and Progress” (New York: 2017) and David Hart and Peter Singer, “Manufacturing USA at DOE: Supporting Energy Innocation.” (Washington: Information Technology and Innovation Institute, 2018). [↑](#endnote-ref-160)
161. For a succinct overview of U.S. economic adjustment programs, see Mark Muro and Joseph Parilla, “Maladjusted: It’s time to reimagine economic ‘adjustment’ programs,” *The Avenue*, January 10, 2017. [↑](#endnote-ref-161)
162. Mark Muro and Amy Liu, “Beyond ‘Amazon Idol’ toward a real regional growth strategy.” *The Avenue,* September 22, 2017. [↑](#endnote-ref-162)
163. Ibid. [↑](#endnote-ref-163)
164. Ibid. [↑](#endnote-ref-164)
165. See Mark Muro, William Galston, and Clara Hendrickson, “Stemming the tide of spatial divergence: neither nostalgia nor neglect will alleviate the geography of discontent,” forthcoming, 2019. [↑](#endnote-ref-165)
166. See *Defense Infrastructure: Communities Need Additional Guidance and Information to Improve Their Ability to Adjust to DOD Installation Closure or Growth*, (Government Accountability Office, 2013); see also <http://www.oea.gov/>. [↑](#endnote-ref-166)
167. Government Accountability Office, *Defense Infrastructure*. [↑](#endnote-ref-167)
168. See, for example, Austin, Glaeser, and Summers, “Saving the Heartland;” Robert Litan, “Metting the Automation Challenge to the Middle Class and the American Project” (Washington: Brookings Institution, 2018); and Neumark, “Rebuilding Communities Job Subsidies.” [↑](#endnote-ref-168)