AUTOMATION and ARTIFICIAL INTELLIGENCE

How machines are affecting people and places

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EXECUTIVE SUMMARY

The power and prospect of automation and artificial intelligence (AI) initially alarmed technology experts, for fear that machine advancements would destroy jobs. Then came a correction of sorts, with a wave of reassurances minimizing their negative impacts.

Now, the discourse appears to be arriving at a more complicated, mixed understanding that suggests that automation will bring neither apocalypse nor utopia, but instead both benefits and stresses alike. Such is the ambiguous and sometimes disembodied nature of the "future of work" discussion.

Which is where the present analysis aims to help. Intended to clear up misconceptions on the subject of automation, the following report employs government and private data, including from the McKinsey Global Institute, to develop both backward- and forward-looking analyses of the impacts of automation over the years 1980 to 2016 and 2016 to 2030 across some 800 occupations. In doing so, the report assesses past and coming trends as they affect both people and communities, and suggests a comprehensive response framework for national and state-local policymakers.

In terms of **current trends**, the report finds that:

1. Automation and AI will affect tasks in virtually all occupational groups in the future but the effects will be of varied intensity—and drastic for only some. The effects in this sense will be broad but variable:

- **Almost no occupation will be unaffected by the adoption of currently available technologies.**
- **Approximately 25 percent of U.S. employment (36 million jobs in 2016) will face high exposure to automation in the coming decades (with greater than 70 percent of current task content at risk of substitution).**
- **At the same time, some 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.**

2. The impacts of automation and AI in the coming decades will vary especially across occupations, places, and demographic groups. Several patterns are discernable:

- **"Routine," predictable physical and cognitive tasks will be the most vulnerable to automation in the coming years.**

  Among the most vulnerable jobs are those in office administration, production, transportation, and food preparation. Such jobs are deemed "high risk," with over 70 percent of their tasks potentially automatable, even though they represent only one-quarter of all jobs. The remaining, more secure jobs include a broader array of occupations ranging from complex, "creative" professional and technical roles with high educational requirements, to low-paying personal care and domestic service work characterized by non-routine activities or the need for interpersonal social and emotional intelligence.

Near-future automation potential will be highest for roles that now pay the lowest wages. Likewise, the average automation potential of occupations requiring a bachelor's degree runs to just 24 percent, less than half the 55 percent task exposure faced by roles requiring less than a bachelor's degree. Given this, better-educated, higher-paid earners for the most part will continue to face lower automation threats based on current task content—though that could change as AI begins to put pressure on some higher-wage "non-routine" jobs.

- **Automation risk varies across U.S. regions, states, and cities, but it will be most disruptive in Heartland states.** While automation will take place everywhere, its inroads will be felt differently across the country. Local risks vary with the local industry, task, and skill mix, which in turn determines local susceptibility to task automation.

  Large regions and whole states—which differ less from one another in their overall industrial compositions than do smaller locales like metropolitan areas or cities—will see noticeable but not, in most cases, radical variations in task exposure to automation. Along these lines, the state-by-state variation of automation potential is relatively narrow, ranging 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 depicted in Map 2 of this report.

  Yet, the map of state automation exposure is distinctive. Overall, the 19 states that the Walton Family Foundation labels as the **American Heartland** have an average employment-weighted automation potential of 47 percent of current tasks, compared with 45 percent in the rest of the country. Much of this exposure reflects Heartland states' longstanding and continued specialization in manufacturing and agricultural industries.

- **At the community level, the data reveal sharper variation, with smaller, more rural communities significantly more exposed to automation-driven task replacement—and smaller metros more vulnerable than larger ones.** The average worker in a small metro area with a population of less than 250,000, for example, works in a job where 48 percent of current tasks are potentially automatable. But that can rise or decline. In small, industrial metros like **Kokomo, Ind.** and **Hickory, N.C.** the automatable share of work reaches as high as 55 percent on average. By contrast, small university towns like **Charlottesville, Va.** and **Ithaca, N.Y.**, or state capitals like **Bismarck, N.D.** and **Santa Fe, N.M.**, appear relatively well-insulated.

  As to 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 in 2030 ranges from 50 percent and 49 percent in less well-educated locations like **Toledo, Ohio** and **Greensboro-High Point, N.C.**, to just 40 percent and 39 percent in high education attainment metros like **San Jose, Calif.** and **Washington, D.C.**

Following Washington, D.C. and San Jose among 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 relatively protected by their specializations in durable professional, business, and financial services occupations, combined with relatively large education and health enterprises.

- **Men, young workers, and underrepresented communities work in more automatable occupations.** In this respect, the sharp segmentation of the labor market by gender, age, and racial-ethnic identity ensures that AI era automation is going to affect demographic groups unevenly.

Male workers appear noticeably more vulnerable to potential future automation than women do, given their overrepresentation in production, transportation, and construction-installation occupations—job areas that have above-average projected automation exposure.

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.

Automation exposure will vary even more sharply across age groups, meanwhile, with the young facing the most disruption. Young workers between the ages of 16 and 24 face a high average automation exposure of 49 percent, which reflects their dramatic overrepresentation in automatable jobs associated with food preparation and serving.

Equally sharp variation can be forecasted in the automation inroads that various racial and ethnic groups will face. Hispanic, American Indian, and black workers, for example, face average current-task automation potentials of 47 percent, 45 percent, and 44 percent for their jobs, respectively, 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 high-exposure occupations like construction and agriculture (Hispanic workers) and transportation (black workers). Black workers have a slightly lower average automation potential based on their overrepresentation in health care support and protective and personal care services, jobs which on average have lower automation susceptibility.

3. To manage and make the best of these changes five major agendas require attention on the part of federal, state, local, business, and civic leaders.

To start with, government must work with the private sector to **embrace growth and technology** to keep productivity and 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. To that end, the appropriate actors need to:

Promote a constant learning mindset
- 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

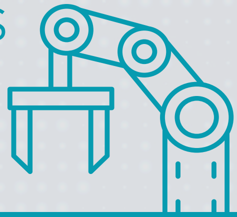
Facilitate smoother adjustment
- Create a Universal Adjustment Benefit to support all displaced workers
- Maximize hiring through a subsidized employment program

Reduce hardships for workers who are struggling
- Reform and expand income supports for workers in low-paying jobs
- Reduce financial volatility for workers in low-wage jobs

Mitigate harsh local impacts
- Future-proof vulnerable regional economies
- Expand support for community adjustment

If the nation can commit to its people in these ways, an uncertain future full of machines will seem much more tolerable.

FIVE POLICY STRATEGIES FOR ADJUSTING TO AUTOMATION



Embrace growth and technology
Run a full-employment economy, both nationally and regionally
Embrace transformative technology to power growth
Promote a constant learning mindset
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
Facilitate smoother adjustment
Create a Universal Adjustment Benefit to support all displaced workers
Maximize hiring through a subsidized employment program
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Mitigate harsh local impacts
Future-proof vulnerable regional economies
Expand support for community adjustment

Source: Metropolitan Policy Program at Brookings

1. INTRODUCTION

Technologists at first issued scary dystopian alarms about the power of automation, including artificial intelligence (AI), to destroy work.

Then came a correction of sorts, with a wave of reassurances that tended to minimize alarm.

Now, the discourse appears to be arriving at a more balanced story that suggests that while the robots are coming they will bring neither an apocalypse nor utopia, but instead both benefits and stress alike.

To the first rosier point, most observers today agree that the recent past may well presage the near future with its reminder that automation in the last 30 years delivered more jobs to the economy than it destroyed, and so holds out significant opportunity.

Automation and AI, in this vein, are increasingly looking like sources of the productivity gains badly needed to secure higher-quality economic growth in the United States. As such, automation could well lift the national economy in the coming years and increase prosperity at a time of uncertainty.

At the same time, though, many commentators now also forecast significant disruption. In this darker portion of the new conventional wisdom, the general consensus now holds that rough times are ahead in the labor market that will cause very real dislocations for many workers even if the total number of jobs holds steady. All of which underscores how mixed, contested, and uncertain is our knowledge about how automation and similar technologies will hit home in the coming years.

Which is where this report aims to help. In order to fill in some of the blanks and provide an overview of automation trends both in the recent past and the near future, the pages that follow develop both backward- and forward-looking analyses of how the advent of digital technologies is already reorienting labor markets and may continue to do so—along with a policy agenda for national and state-local response.

The analysis begins by defining and conceptualizing automation. 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. Throughout, the focus is on areas of potential occupational stress rather than on net employment totals. Special attention is applied, moreover, to digging beneath the national top-line statistics to explore industry, geographical, and demographic variations. Finally, the report concludes by suggesting a framework and recommendations for national and state-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.

It says a lot, for example, that the mass adoption of automation in the form of pervasive digitalization in the years since 1980 brought not mass joblessness but a slight increase in the availability of jobs. Such gains, if reprised in the future, would be an important counter to excessive fear.

Yet, a future that resembles the recent past is not necessarily cause for cheer. As the retrospective analysis here suggests, the first era of digital automation was one of traumatic change, 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. That our forward-looking analysis projects more of the same in the next decade-plus will not, therefore, be very 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 along with the reassurance that automation has the potential to be beneficial even while it remains disruptive.

2. AUTOMATION: WHAT IT IS, HOW TO CONCEPTUALIZE IT, HOW IT IMPACTS WORKERS

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

What is 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. Think of inventions like the steam engine, electricity, and information technologies. Other 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.

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—but, the share of the population engaged in work actually rose as new demand engendered new products, services, and work.

However, 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 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

How should we conceptualize automation as an economic matter for analysis? To understand the impact of automation on employment, one must first be able to quantify it as an economic activity. Yet this remained a practical and conceptual challenge for many years.[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] 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).

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] 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]

How does automation impact 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 these 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]

- **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 advancement, it is unlikely that machines will be able to substitute for *all tasks* in any one occupation.[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. Such productivity gains can do much to lift economies and increase prosperity at a time when both aging and falling birthrates are acting as a drag on growth.[7]

- **Automation can increase 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.[8]

- **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.[9] Note, too, that in the IT 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).[10]

- **Technological possibility is not the same as technological reality.** In this regard, it is a mistake to equate technological potential with likely projected outcomes. To see this consider that McKinsey & Company estimates that the U.S. currently achieve 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.[11]

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.[12] 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 machines complement the tasks that remain for humans, 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 in the occupation.

- **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, 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 essential 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."[13] As an example, James Bessen of Boston University describes huge declines in the price of cloth in the 1800s due to mechanized looms, which led to a net increase in textile jobs. As the price of clothing declined, the ability of households to expand wardrobes exploded, therefore increasing the demand for weavers even in the face of substantial workplace automation.[14]

The second countervailing dynamic 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 need for logistics 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.[15]

In sum, recent scholarship provides an incisive framework for thinking about the impacts of automation and AI on people and 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.[16] As a result, the total effect of these crosscutting patterns can be hard to predict.[17]

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 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 affected 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.[18] 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.[19] 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 influenced 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."[20] 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 by Economic Modeling Systems (EMSI)—a data vendor specializing in labor markets.[21] EMSI provided the data 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.)[22]

With these data in hand, the automation potential of each occupation from McKinsey was combined with localized employment data for occupations and industries from EMSI and Moody's Analytics, respectively, to produce employment-weighted automation potential estimates for every geography and industry grouping of interest.

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.[23] These efforts stem 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.[24] 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 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.[25] So we do not show how many and where new jobs will emerge. 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 previously.[26] 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.

Second, 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.[27]

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 others will. 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 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.

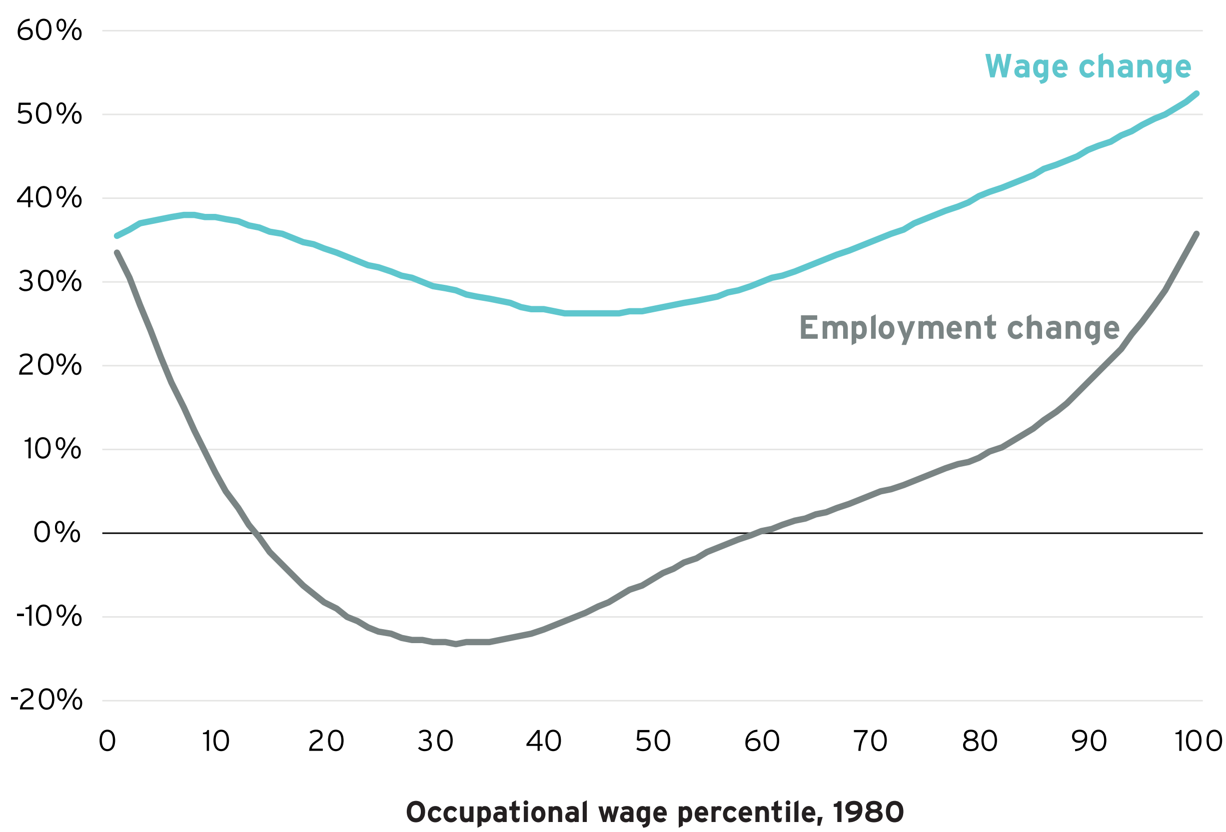
1. Overall employment has grown in the IT era nationally, but the middle of the wage continuum has been "hollowed out"—with changes in employment and wages greatest at the high and low ends of the wage distribution.

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

FIGURE 1

Wage and employment growth has been slowest in middle-wage jobs

Percent change, United States, 1980-2016



Note: Figures have been smoothed using a LOWESS regression
Source: Brookings analysis of Autor (2015), US Census Bureau, IPUMS data

adoption and processing speed were realized.[28] 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 advancement.

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.[29] Nor is the United States alone in facing this dynamic—this same trend has also been documented across the whole of Western Europe.[30]

Figure 1, derived from Autor and Dorn, illustrates these trends in the United States. As such, the graph plots smoothed changes in employment (the dark gray line) and wages (the light green 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 predominantly 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 contemporaneousness of the U-shaped employment and wage curves of the 1980 to 2016 period and the rise of digital automation might just be a coincidence. Why does it increasingly appear that automation caused them? Data and the task framework provide some insight. Figure 2 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. Nonetheless, 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. 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.[31]

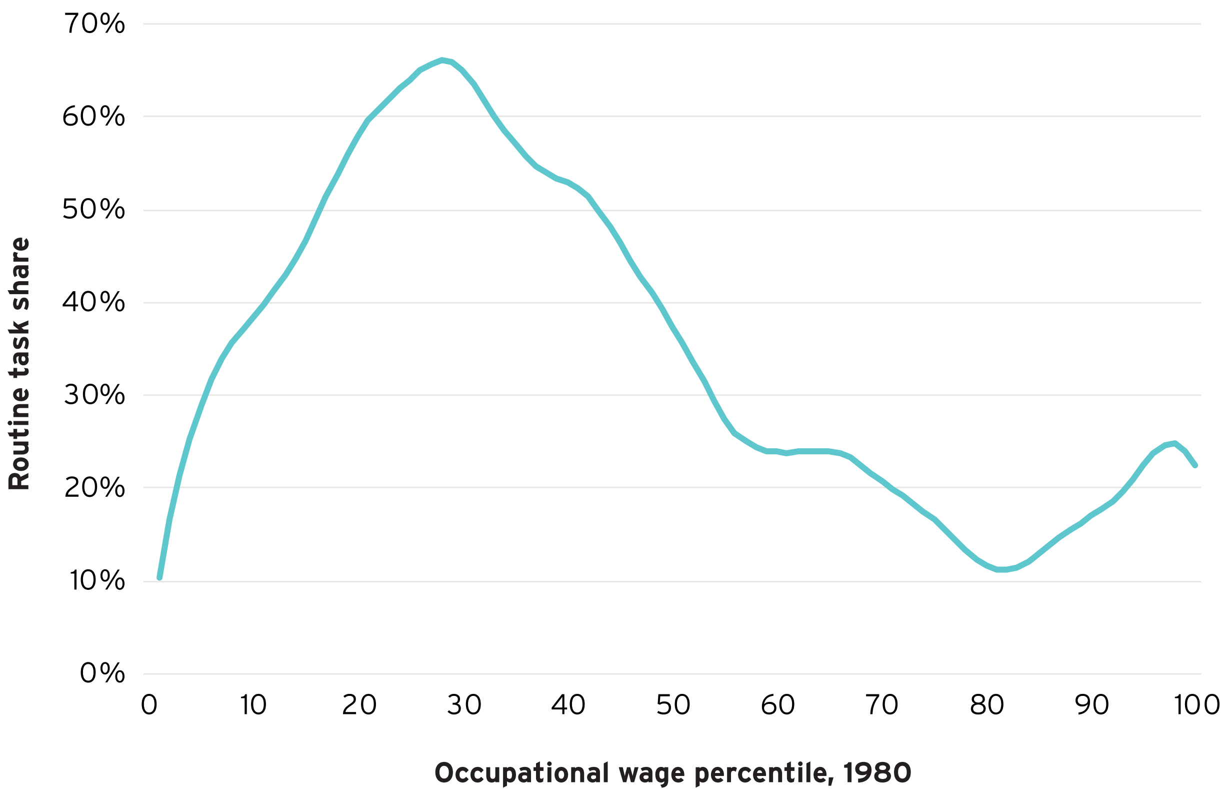
The takeaway: Automation has substituted for many jobs, but not all jobs—and it has complemented much work and so supported growth. In this fashion, technological progress in the years from 1980 to 2016 drove a pronounced polarization of U.S. employment and wages that has only shown signs of easing somewhat in the last few years.[32] Central to how this has played out is the fact that machine substitution for human tasks requires an understanding of workplace activities 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.

FIGURE 2

Slow growing occupations were also the most routine task-intensive

United States, 1980



Note: Figures have been smoothed using a LOWESS regression
Source: Autor and Dorn (2013)

3. Manufacturing and office administration-oriented regions 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 IT era.

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 Map 1 shows—with virtually all regions except the Great Plains containing commuting zones with substantial rote or routine task content in occupations.

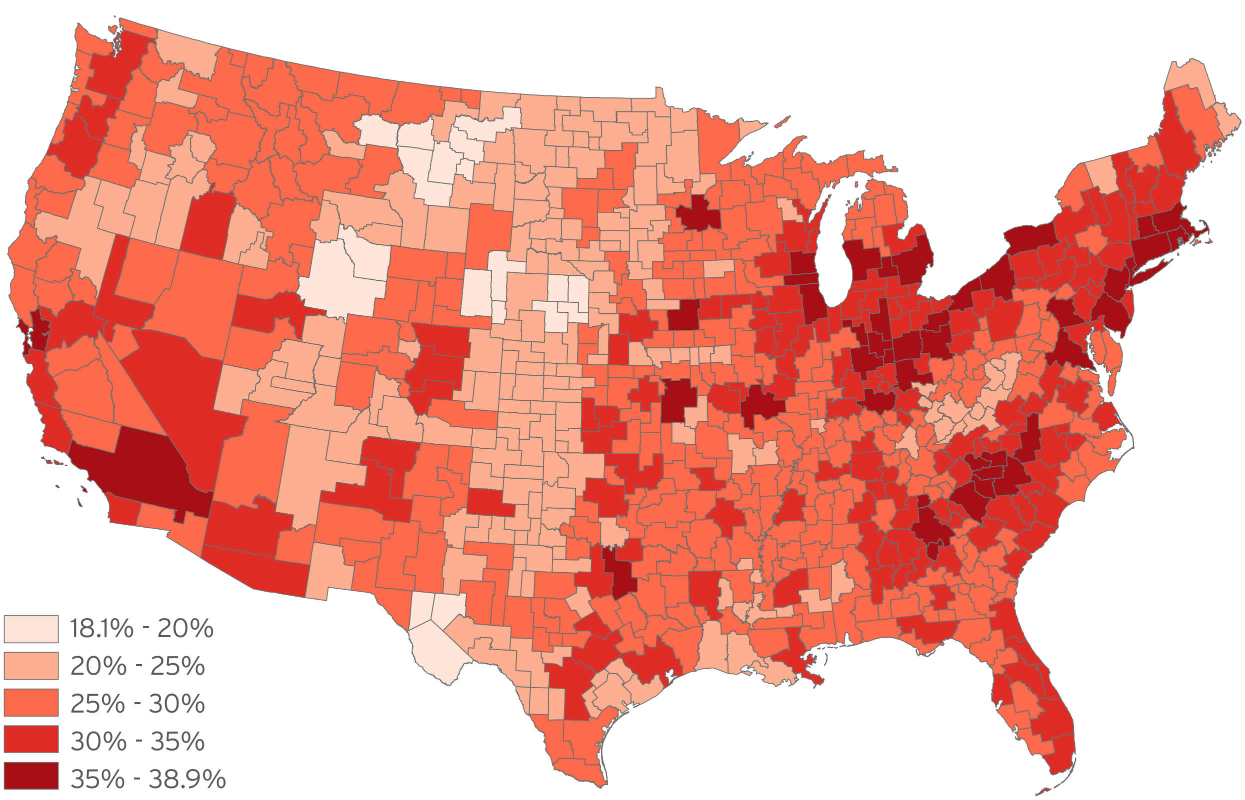
Yet with that said, the incidence of routine-oriented work differed widely across places in 1980.

Some of 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. Commuting zones (CZs) like **Detroit** (37.7 percent), **Greensboro, N.C.** (37.6 percent), and **Providence, R.I.** (37.0 percent) are indicative of this pattern. Moreover, there is 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

MAP 1

Routine occupation share of employment by commuting zone, 1980

Employment share, United States, 1980



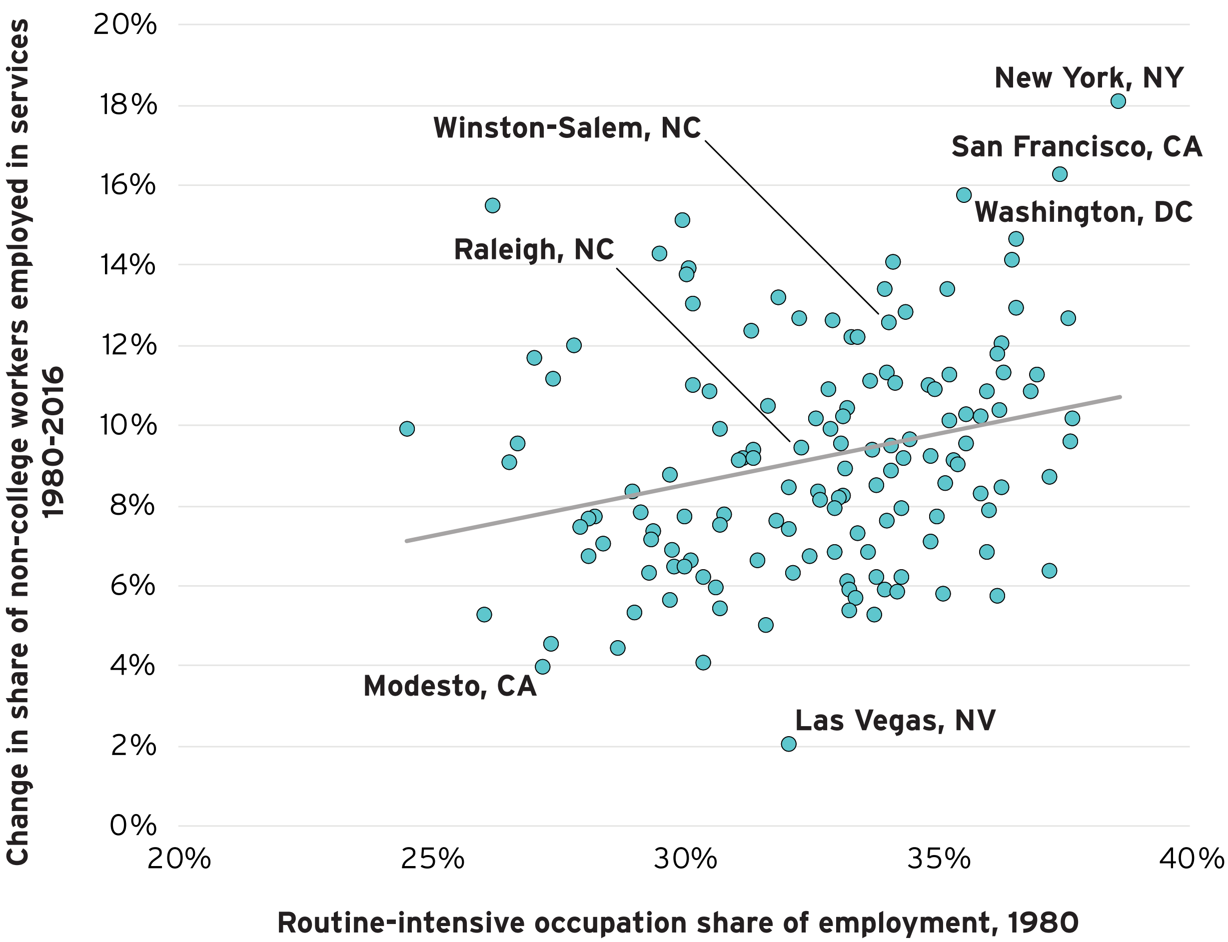
Source: Brookings analysis of Autor and Dorn (2013) other words, the highest routine-intensive regions were also the highest manufacturing-intensive).[33]

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.

FIGURE 3

Routine-intensive jobs were largely replaced by lower paying service jobs

Dots represent the 140 commuting zones with over 500,000 residents



Source: Brookings analysis of Autor and Dorn (2013)

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.[34] This drove a decline in routine jobs nationally, which meant 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 above 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, 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, food service, 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 IT 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) all had 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

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

To shed some light on this, the coming 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.

Looking forward, 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 today's machines and that likely will remain so in the near future. This work that machines cannot readily do now 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)[35]

Given these factors, 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. Such 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 decisionmaking, 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.

To show what this looks like, Table 1 displays some representative occupations and their associated task-level automation potential, average wages, and educational requirements.

Similarly, Figure 4 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. 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, entertainment, health care, and social and community services (those to the left of the bar chart) 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 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.

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 5 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.[36]

TABLE 1

Current-task automation potential, average wages, and educational requirements for representative occupations

Occupation	Average wage	Automation potential	Typical education required
Packaging and Filling Machine Operators and Tenders	$31,000	100%	Less than Bachelor's Degree
Food Preparation Workers	$23,000	91%	Less than Bachelor's Degree
Payroll and Timekeeping Clerks	$44,000	87%	Less than Bachelor's Degree
Light Truck or Delivery Services Drivers	$35,000	78%	Less than Bachelor's Degree
Computer Network Support Specialists	$68,000	62%	Less than Bachelor's Degree
Medical Assistants	$33,000	54%	Less than Bachelor's Degree
Retail Salespersons	$27,000	47%	Less than Bachelor's Degree
Computer Programmers	$85,000	38%	Bachelor's Degree or More
Registered Nurses	$72,000	29%	Bachelor's Degree or More
Maids and Housekeeping Cleaners	$24,000	18%	Less than Bachelor's Degree
Home Health Aides	$24,000	11%	Less than Bachelor's Degree
Software Developers, Applications	$105,000	8%	Bachelor's Degree or More
Management Analysts	$92,000	4%	Bachelor's Degree or More
U.S. total	**$49,600**	**46%**	

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

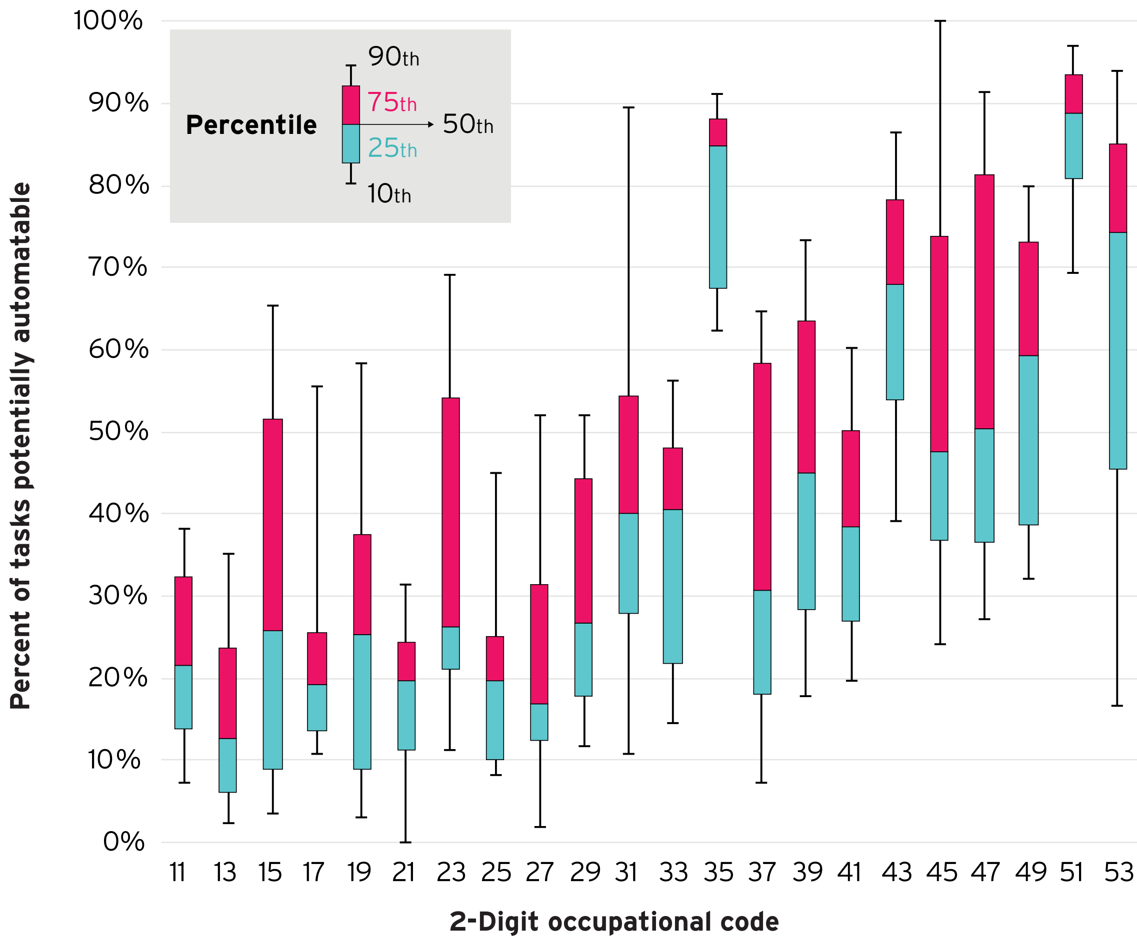
Over the next few decades, approximately 25 percent of U.S. employment (36 million jobs in 2016) will have experienced high exposure to automation (with greater than 70 percent of current task content at risk of substitution. At the same time, the data suggest that another 36 percent of U.S. employment (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, 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 than in the past.

FIGURE 4

Large variation in automation exposure exists across occupations

6-digit SOC-code occupations within each 2-digit SOC group



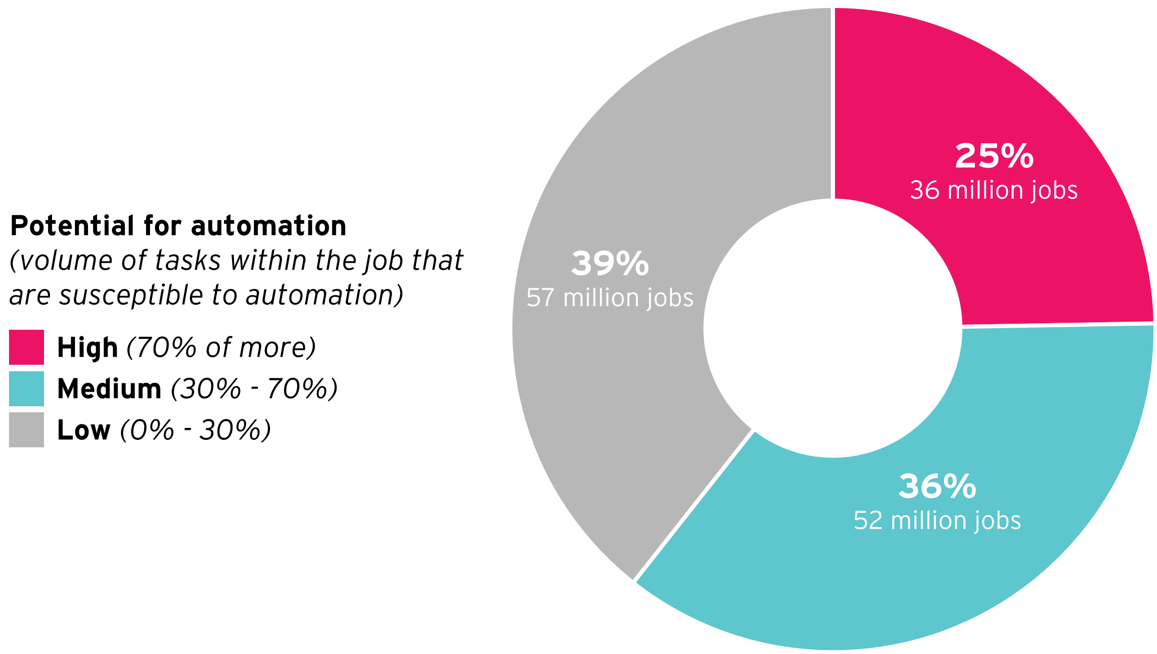
Note: 11=Management Occupations; 13=Business and Financial Operations Occupations; 15=Computer and Mathematical Occupations; 17=Architecture and Engineering Occupations; 19=Life, Physical, and Social Science Occupations; 21=Community and Social Services Occupations; 23=Legal Occupations; 25=Education, 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

Source: Brookings analysis of BLS, Census, EMSI, Moody's, and McKinsey data

FIGURE 5

Most jobs are not highly susceptible to automation

Shares of employment by automation potential



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

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 6 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 and wages with the earlier one displaying 1980 wage and employment growth against wage percentiles (which implied automation potential). 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 could happen.[37]

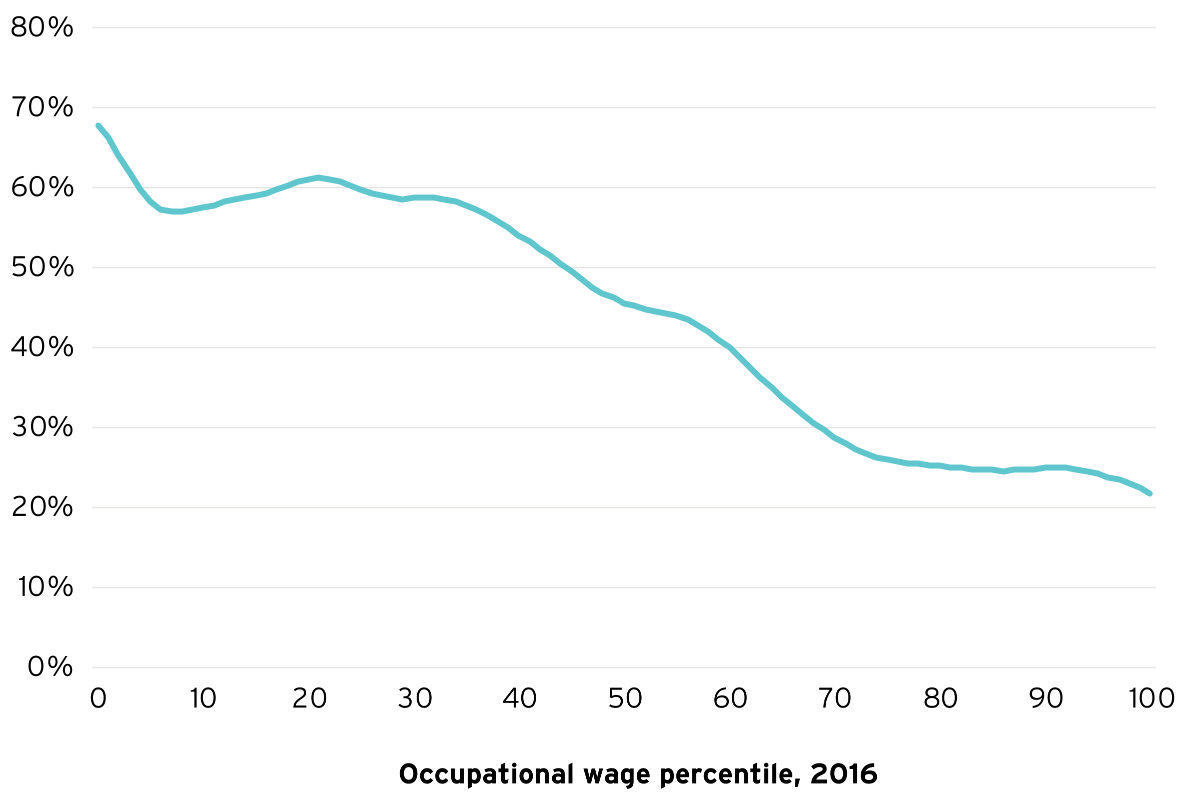
Undoubtedly, though, it is the changed situation of occupations in the bottom third of the wage distribution that stands out when the AI era is contrasted to the earlier IT era. Some occupations with relatively low routine task-intensity—bus and taxi drivers, wait staff, carpenters, electricians—and 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.

FIGURE 6

The lowest wage jobs are the most exposed to automation

Automation potential, United States, 2016



Note: Figures have been smoothed using a LOWESS regression
Source: Brookings analysis of BLS, Census, EMSI, and McKinsey data

TABLE 2

Current-task automation potential, average wages, and educational requirements for representative occupations

Occupation group	Average wage	Automation potential	Typical education required
Food Preparation and Serving Related Occupations	$23,900	81%	Less than Bachelor's Degree
Production Occupations	$37,200	79%	Less than Bachelor's Degree
Office and Administrative Support Occupations	$37,300	60%	Less than Bachelor's Degree
Farming, Fishing, and Forestry Occupations	$27,800	56%	Less than Bachelor's Degree
Transportation and Material Moving Occupations	$36,100	55%	Less than Bachelor's Degree
Construction and Extraction Occupations	$48,900	50%	Less than Bachelor's Degree
Installation, Maintenance, and Repair Occupations	$46,700	49%	Less than Bachelor's Degree
Sales and Related Occupations	$40,600	43%	Less than Bachelor's Degree
Healthcare Support Occupations	$30,500	40%	Less than Bachelor's Degree
Legal Occupations	$106,000	38%	Bachelor's Degree or More
Computer and Mathematical Occupations	$87,900	37%	Bachelor's Degree or More
Protective Service Occupations	$45,800	36%	Less than Bachelor's Degree
Personal Care and Service Occupations	$26,500	34%	Less than Bachelor's Degree
Healthcare Practitioners and Technical Occupations	$79,200	33%	Bachelor's Degree or More
Life, Physical, and Social Science Occupations	$72,900	32%	Bachelor's Degree or More
Management Occupations	$118,000	23%	Bachelor's Degree or More
Community and Social Services Occupations	$47,200	22%	Bachelor's Degree or More
Building and Grounds Cleaning and Maintenance Occupations	$28,000	21%	Less than Bachelor's Degree
Arts, Design, Entertainment, Sports, and Media Occupations	$58,400	20%	Less than Bachelor's Degree
Architecture and Engineering Occupations	$84,300	19%	Bachelor's Degree or More
Education, Training, and Library Occupations	$54,500	18%	Bachelor's Degree or More
Business and Financial Operations Occupations	$75,100	14%	Bachelor's Degree or More
U.S. total	$49,600	46%	
Occupations requiring Less than Bachelor's Degree	$36,500	55%	
Occupations requiring Bachelor's Degree or More	$80,100	24%	

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

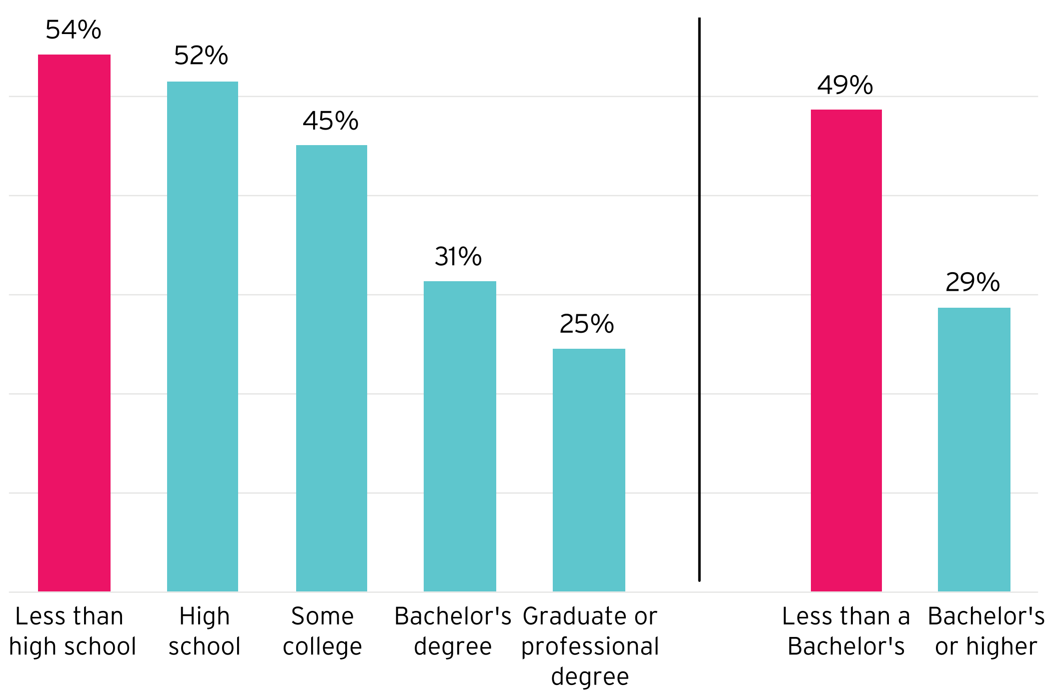
Similar results surface when looking at the average automation potential of *workers* by actual educational attainment, rather than the estimated educational requirements of the roles they inhabit. By that measure, workers without a bachelor's degree are on average employed in jobs with task automation potential of 49 percent. Some 29 percent of such workers are currently employed in jobs with a 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, automation 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. In this regard, the self-checkout kiosk and AI concierge may soon loom as large as industrial robots as labor-market disturbances. 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.

FIGURE 7

Non-college workers will see greater job change from automation

Average automation potential by worker educational attainment, 2016



Source: Brookings Analysis of 2016 American Community Survey 1-Year microdata

TABLE 3

Automation potential and labor productivity growth for 20 major "industry groups"

Industrial family	Annual labor productivity growth, 2000-16	Automation potential
Accommodation and Food Services	-0.8%	73%
Manufacturing	2.9%	59%
Transportation and Warehousing	0.2%	58%
Agriculture, Forestry, Fishing and Hunting	3.3%	57%
Retail Trade	0.9%	53%
Mining, Quarrying, and Oil and Gas Extraction	3.2%	51%
Other Services (except Public Administration)	-1.6%	49%
Construction	-1.0%	47%
Wholesale Trade	1.7%	44%
Utilities	-0.2%	43%
Finance and Insurance	1.1%	42%
Arts, Entertainment, and Recreation	0.4%	41%
Administrative and Support and Waste Management and Remediation Services	2.1%	41%
Real Estate and Rental and Leasing	2.1%	40%
Government	-0.1%	37%
Health Care and Social Assistance	0.2%	36%
Information	6.2%	35%
Management of Companies and Enterprises	0.1%	34%
Professional, Scientific, and Technical Services	0.9%	34%
Educational Services	-0.7%	27%
U.S. total	**0.8%**	**46%**

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

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.[38] 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 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—will experience the opposite. Of course, much remains unpredictable. Technological possibility is not technological reality and we are unable to forecast how 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 IT era changes.

While automation will 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 or cities—will see noticeable but not in most cases radical variations in task exposure to emerging technologies. Compounding this is the fact that one of the most ubiquitous industries—food and accommodation services—is an outlier in terms of high automation potential.

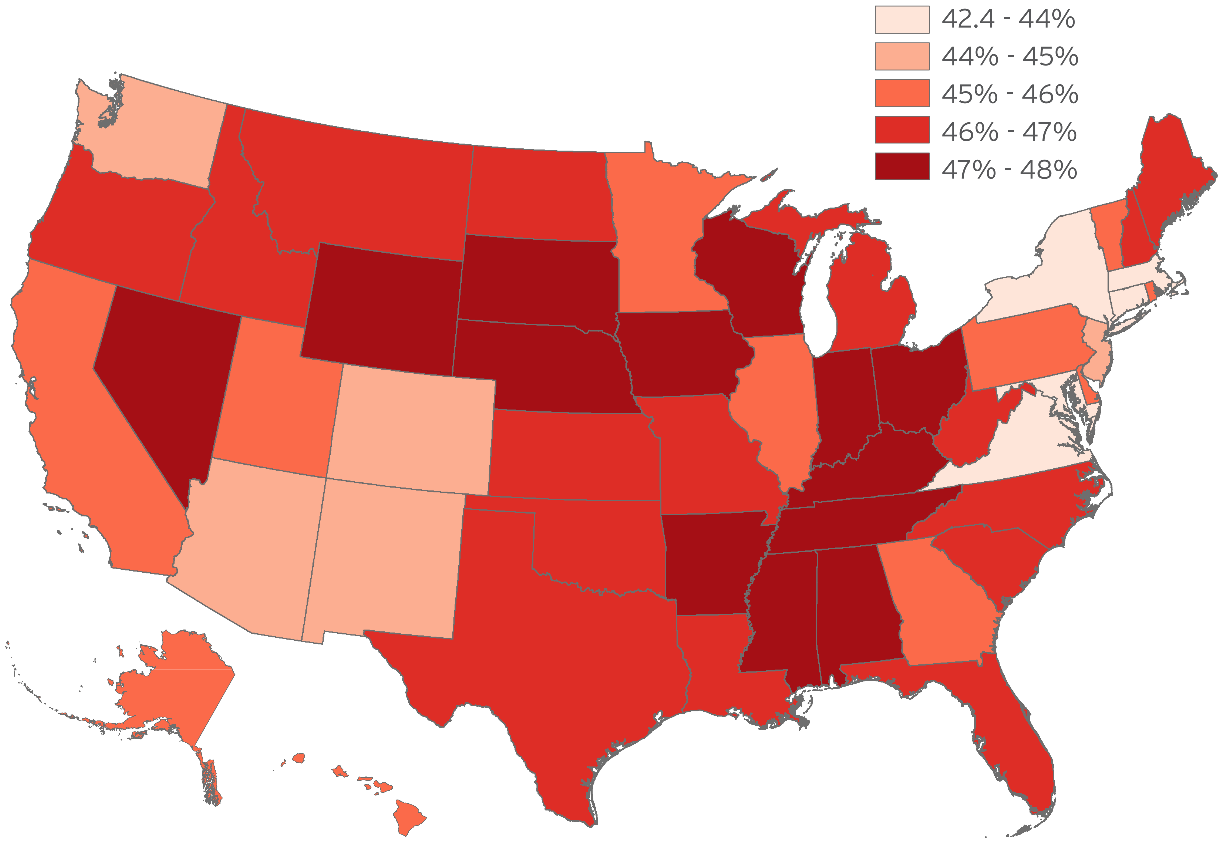
Along these lines, the state-by-state variation of automation potential is relatively narrow, and ranges from 48.7 and 48.4 percent of the employment-weighted task load in **Indiana** and **Kentucky** to 42.9 and 42.4 percent in **Massachusetts** and **New York,** as is depicted in Map 2.

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.[39] 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 past and present exposure reflects the region's longstanding and continued specialization 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.[40]

MAP 2

Average automation potential by state

2016



Source: Brookings analysis of BLS, Census, EMSI, Moody's, and McKinsey data

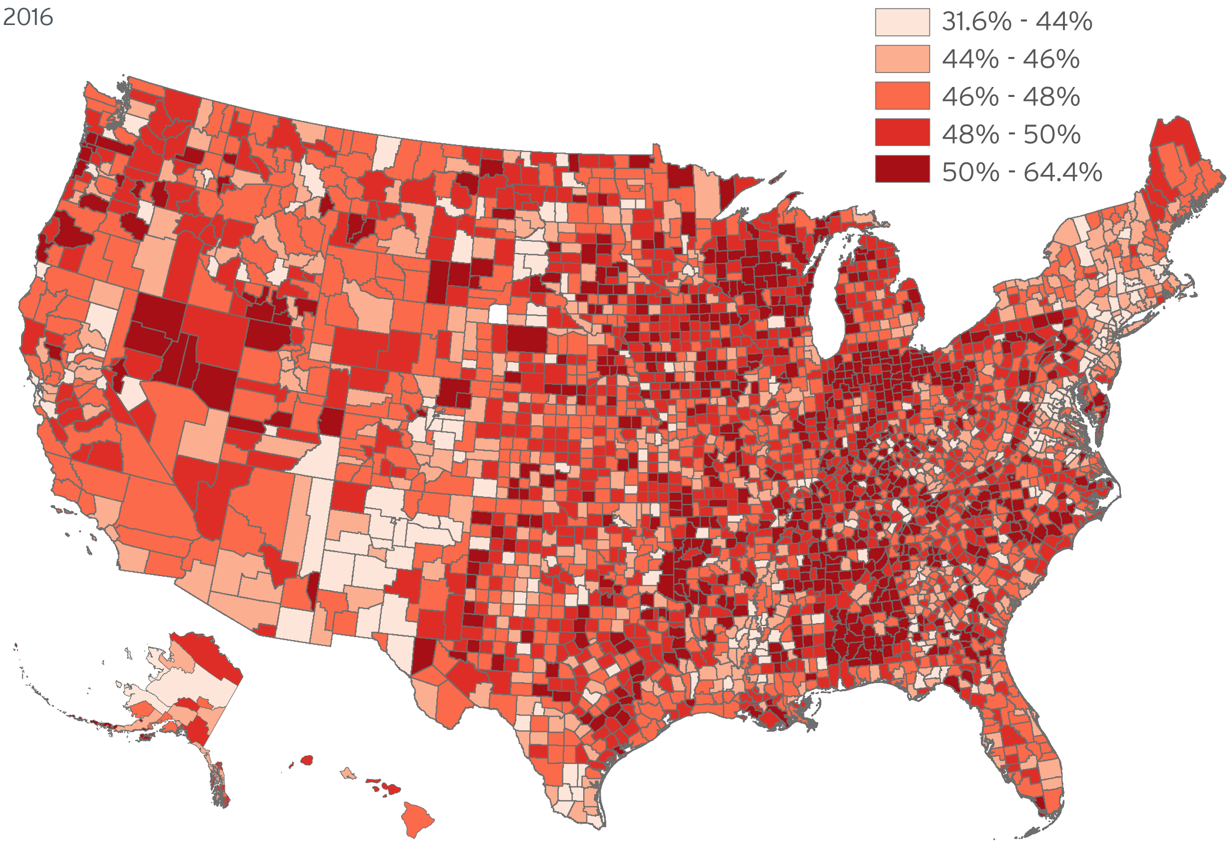
In contrast, states like Massachusetts, **Maryland**, and **Connecticut**—all with bachelor's degree attainment levels in excess of 38 percent—turn out to have lower automation exposures of 44 percent or less.

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 Upper 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. Similarly, exposure levels along the **Boston-Washington** corridor and along the **West Coast** appear relatively muted.

In short, many places that contended with significant dislocation from IT era automation in sectors like manufacturing and transportation during the 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 era technologies. At the same time, the future of automation looks notably different from how it unfolded earlier 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.

MAP 3

Average automation potential by county
2016



Source: Brookings analysis of BLS, Census, EMSI, Moody's, and McKinsey data

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

Turning to the community level, the data reveal variation that is more pronounced.[41] 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 8 reveals the level of automation exposure for six types of counties, arrayed by the size and urban classification of their local communities.

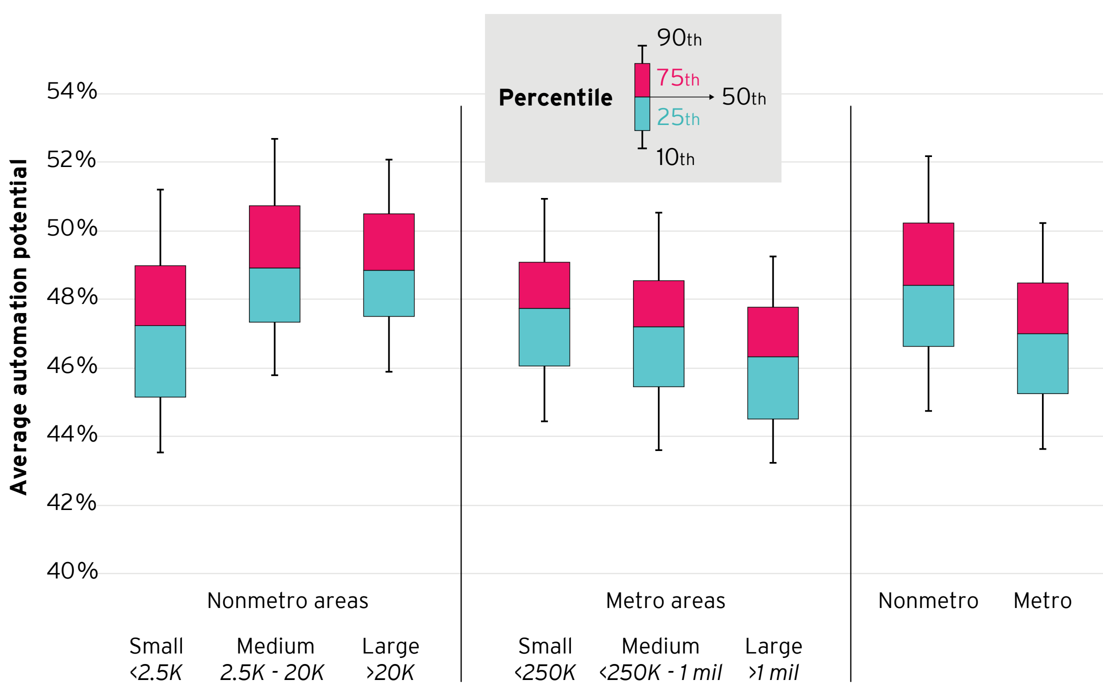
Right off, the figure displays that in general, current-task automation potential declines for counties as population rises, with only the most thinly populated counties being the exception. Roughly three-quarters of all counties in metropolitan areas have on average lower automation exposure than the 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 works 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 places have historically been specialized in routine-intensive

FIGURE 8

Smaller, more rural places will face heightened automation risks

County distribution by community size type, 2016



Source: Brookings analysis of BLS, Census, EMSI, Moody's, and McKinsey data

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.** and **Santa Fe, N.M.**

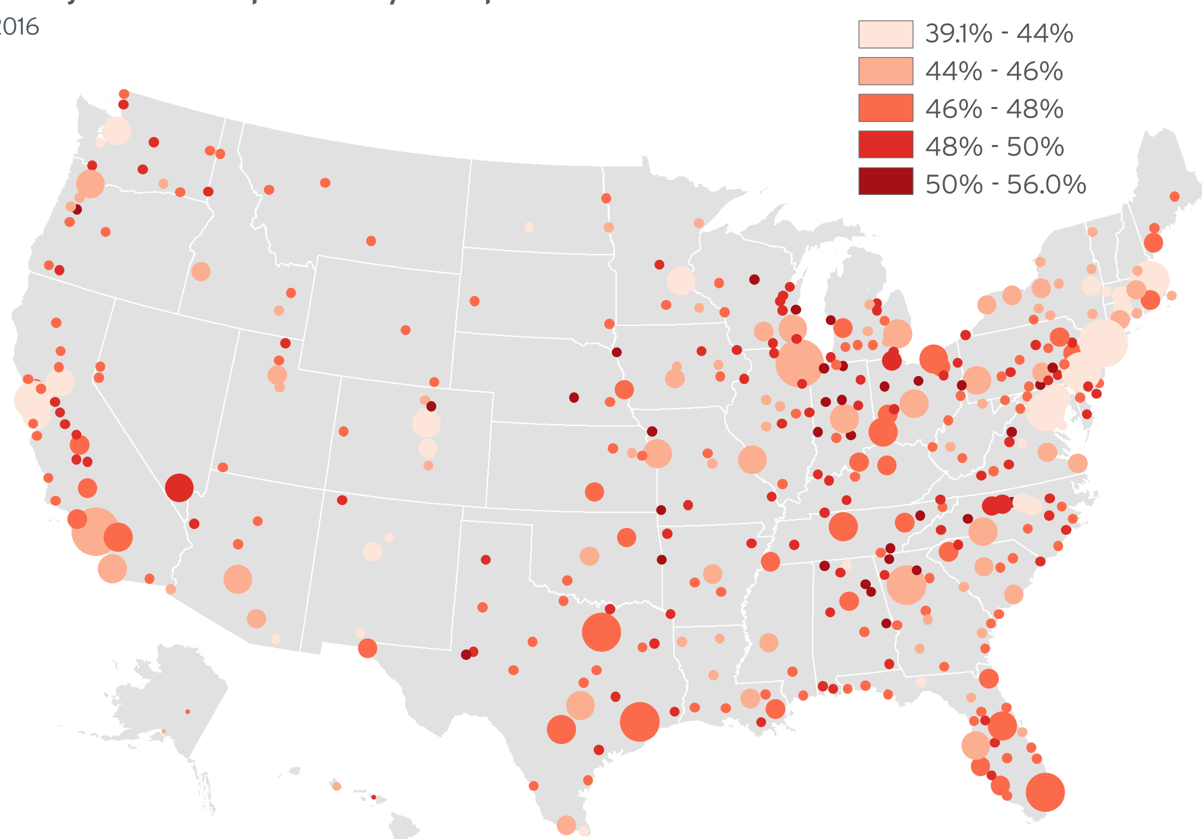
As to how this plays out across the 100 largest metropolitan areas, it is also clear that while the risk of current-task automation will be widely distributed, it won't be evenly spread. Among this subset of key metro areas, educational attainment will prove decisive in shaping how local labor markets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

Following Washington, D.C. and San Jose among 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, business, and financial services occupations combined with relatively large education and health enterprises.

MAP 4

Average automation potential by metropolitan area

2016



Source: Brookings analysis of BLS, Census, EMSI, Moody's, and McKinsey data

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, accommodations, 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.[42] The present automation data fits that story. As is visible in the scatterplot Figure 9, 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

TABLE 4

Top 15 and bottom 5 metropolitan areas by educational attainment, 2016

Rank	Metropolitan area	Share of adults with a BA or higher	Share of jobs in occupations with high automation exposure
1	Washington-Arlington-Alexandria, DC-VA-MD-WV	50.2%	17.7%
2	San Jose-Sunnyvale-Santa Clara, CA	50.1%	18.6%
3	San Francisco-Oakland-Hayward, CA	48.5%	21.8%
4	Raleigh, NC	47.2%	21.5%
5	Durham-Chapel Hill, NC	47.0%	19.3%
6	Boston-Cambridge-Newton, MA-NH	46.9%	20.9%
7	Madison, WI	46.6%	22.2%
8	Bridgeport-Stamford-Norwalk, CT	46.6%	21.1%
9	Austin-Round Rock, TX	42.8%	21.8%
10	Denver-Aurora-Lakewood, CO	42.5%	22.3%
11	Seattle-Tacoma-Bellevue, WA	42.0%	23.2%
12	Minneapolis-St. Paul-Bloomington, MN-WI	40.5%	23.5%
13	Baltimore-Columbia-Towson, MD	39.5%	20.4%
14	New York-Newark-Jersey City, NY-NJ-PA	39.0%	20.5%
15	Portland-Vancouver-Hillsboro, OR-WA	38.9%	24.4%
...	...	...	...
96	Fresno, CA	20.2%	25.1%
97	Lakeland-Winter Haven, FL	20.1%	28.9%
98	McAllen-Edinburg-Mission, TX	18.3%	23.2%
99	Stockton-Lodi, CA	16.7%	28.7%
100	Bakersfield, CA	16.3%	23.2%

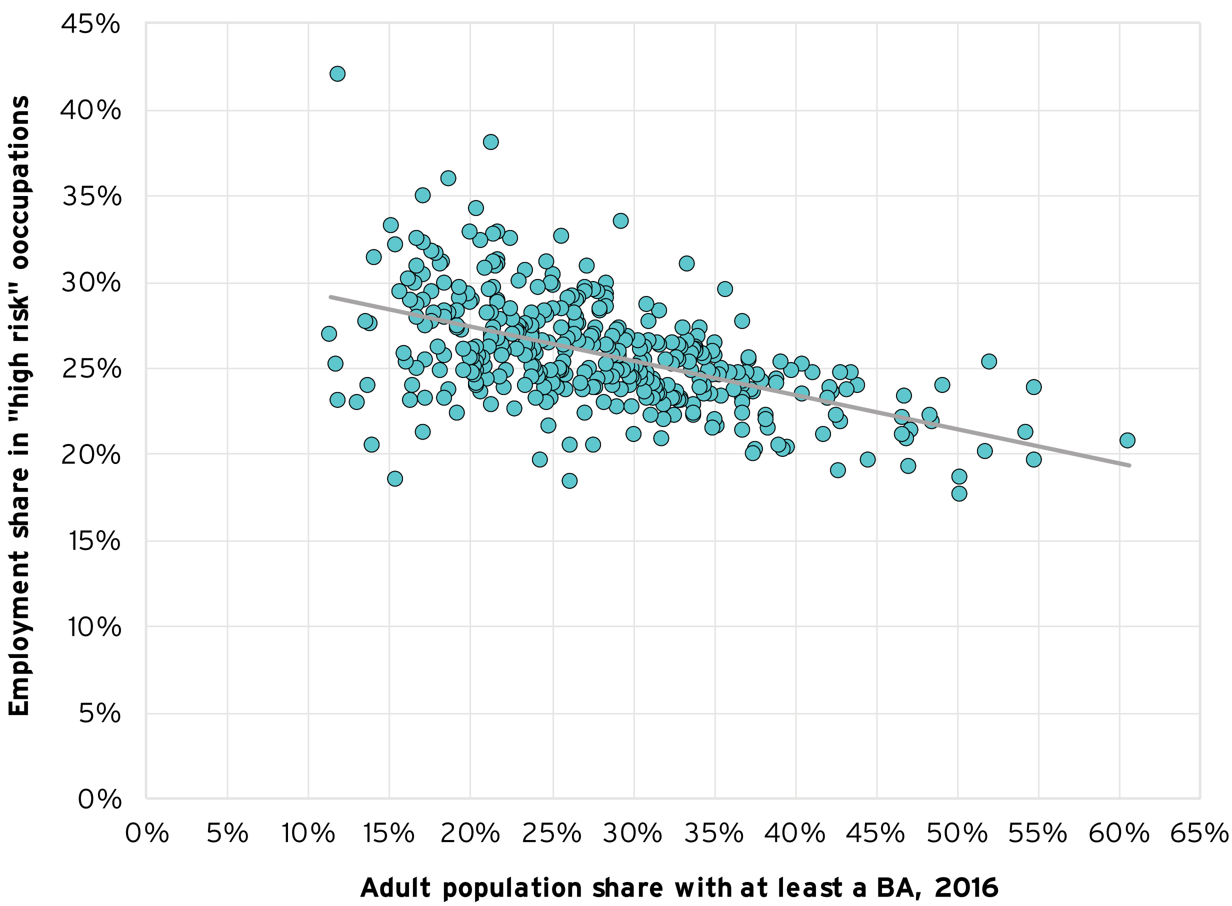
Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data

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 heading for significant disruption.

FIGURE 9

More educated metros are less exposed to task change from automation

Metropolitan areas, 2016



Note: "High risk" occupations have an automation potential of at least 70 percent
Source: Brookings analysis of BLS, Census, EMSI, Moodys, and McKinsey data

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

There is, finally, 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 in different ways; they are also going to affect demographic groups unevenly.

In this respect, 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 the AI era 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.

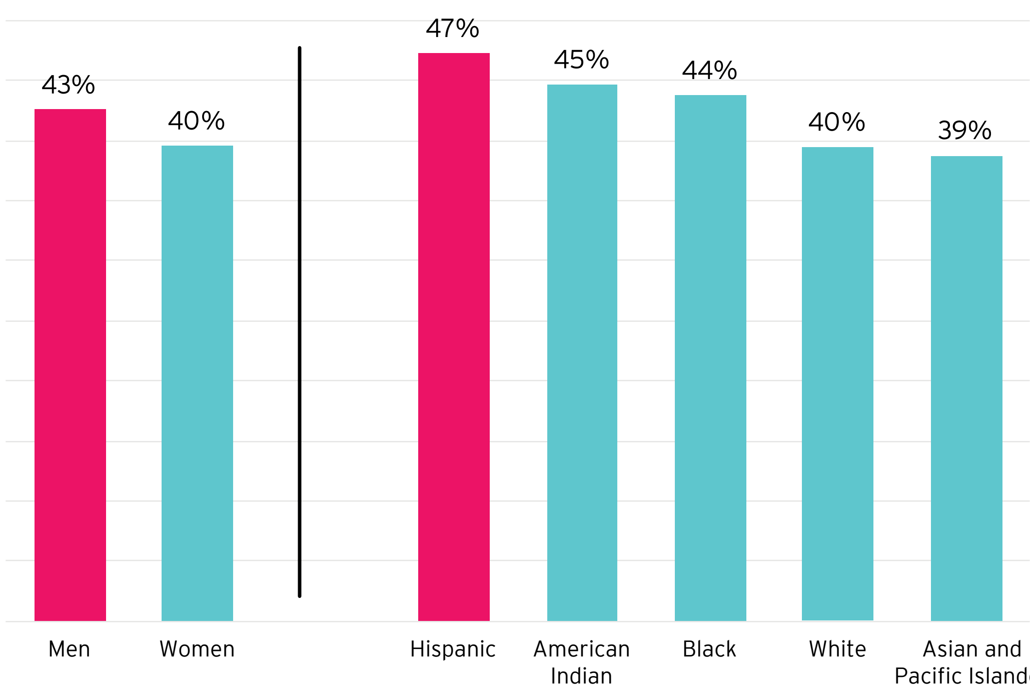
Male workers, to begin with, appear noticeably more vulnerable to potential future automation than women do. Such overexposure reflects the fact than men are significantly overrepresented in occupations with higher automation risk of current tasks.

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

FIGURE 10

Automation exposure breaks sharply along demographic lines

Average automation potential by gender and race, 2016



Source: Brookings analysis of 2016 American Community Survey 1-Year microdata occupational groups with current task 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 might. The average male worker, in this respect, 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 counterpoise 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, meanwhile, with the young facing the most 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.

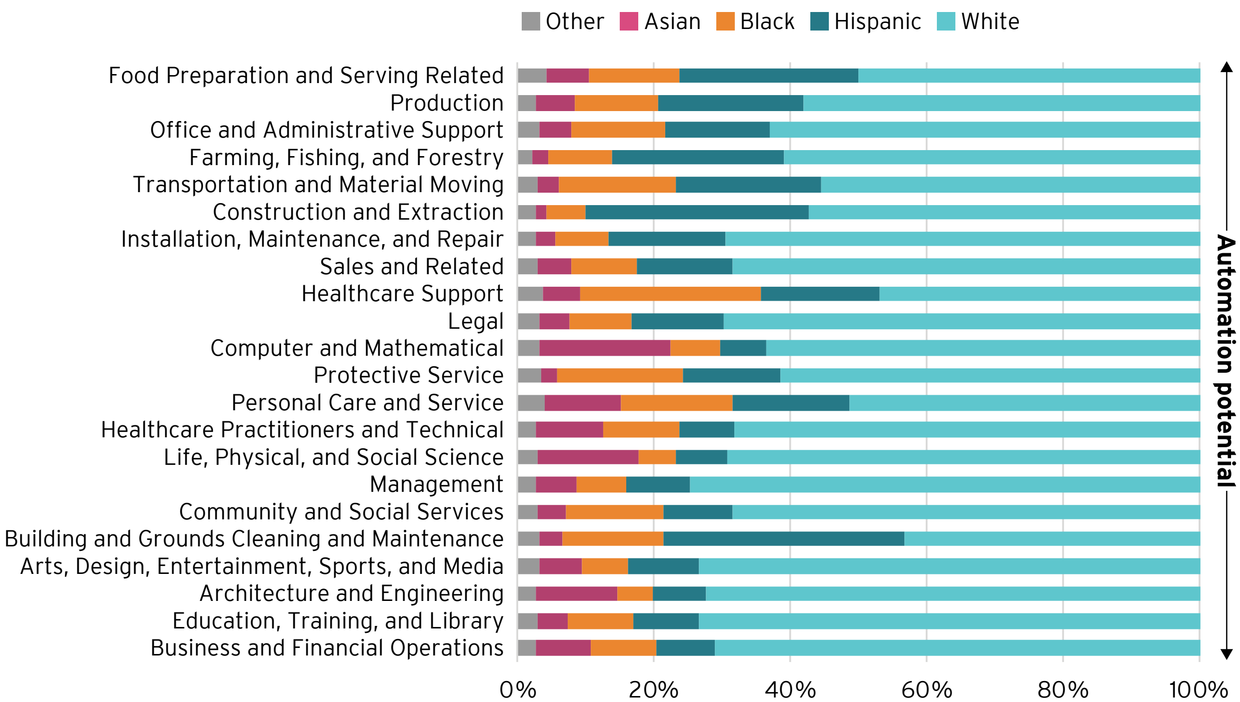
Underlying these differences is the stark over- and underrepresentation of racial and ethnic groups in particular occupational families that face elevated exposure to current-task automation. Hispanic workers, for instance, account for 15.5 percent of the American labor force and yet represent 32.6 percent of the workforce in construction and extraction trades. These jobs could see half of their current tasks automated in the AI era. By contrast, Hispanic workers perform less than 10 percent of education or managerial jobs. 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.

FIGURE 11

Black and Hispanic workers are concentrated in more automatable occupations

Shares of occupation group, 2016



Source: Brookings analysis of American Community Survey 1-year microdata

5. IMPLICATIONS: STRATEGIES FOR ADJUSTING

Automation, forever a major determinant of the nature and availability of work, will continue to reshape the work people do and the opportunities they are afforded. Whether this should be alarming or only cause for slight anxiety depends.

That the near future of automation may well resemble the near past should be somewhat reassuring.

It is encouraging, for example, that the likely future dynamics of job losses and gains are increasingly better understood and project continuous task creation as well as destruction rather than a one-sided apocalypse of permanent unemployment.

If the past is prologue, as this analysis suggests it might be, the labor market will continue to evolve, and the demand for both existing and new forms of work will continue indefinitely—meaning the trade-off of automation and employment will prove a false dichotomy.

And yet, a future that resembles the recent past is hardly cause for cheer. As the retrospective analysis above suggests, the first era of digital automation was one of traumatic change in the labor market for many, defined especially by the "hollowing out" of the labor-market middle, with employment and wage gains coming only at the high and low ends of the skill distribution. Such dynamics have led to a social, economic, and political crisis in the U.S.

That our analysis projects more of the same in the next decade-plus argues, then, for vigilance on several fronts.

In the foreground is the matter of growth and employment:

- Nothing guarantees there will be enough aggregate economic growth going forward to mitigate future dislocation with sufficient job openings. Such growth is necessary to offset displacement but it is not a certainty.

Beyond that, government, business, and society will in any event need to attend to at least four employment and labor market disruptions:

- While full automation will likely be modest, partial task substitution and change within occupations will be widespread. That means most workers will need to continually learn and adapt on the job and to seek new positions.

- Steady, widespread disruption will require sometimes-painful "adjustment" of workers, occupations, and places to new situations as they reorient from existing tasks and jobs to new ones.

- Even with just 25 percent of workers projected to see 70 percent of the task content of their jobs disappear, millions of workers will face substantial work crises, dislocation, and stints of unemployment or long-term displacement. Lower-education and lower-skill workers in routine-manual occupations like manufacturing, transport, and food and accommodation will be especially vulnerable.

- Geographies with a particularly high concentration of automatable jobs will be disproportionately impacted, and spillover effects could harm entire communities.

So while our analysis shows that 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 affected, and much will need to be done to mitigate the coming stresses.

Five major agendas require attention, therefore, as the nation moves into the AI era 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**. Overall, the nation needs to get much better at 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.[43] In conditions of widespread hiring, workers will have an easier time of maintaining employment or transitioning from one job to another—a critical requirement for 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.[44] As a result, wages have stagnated and income inequality has grown.

What's needed with new uncertainties looming, then, is more demand-support through monetary policy (including by lower interest rates) over longer time periods, such as it has been through the 2010s.

Given this, and given the growing role of automation in the labor market, multiple analysts have correctly argued that the federal government should **appoint Federal Reserve governors who focus more on full employment** than on fighting inflation.[45] A full-employment economy, both national and regionally, will help minimize the dislocations associated with the next rounds of automation.[46] Adjustment and reemployment will proceed far more smoothly if there are plentiful job openings, after all.

National monetary policy is a necessary but, by itself, insufficient tool for bringing full employment to every area, however. Also essential, 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.[47] Along these lines, governments should **boost job creation through public investment** in areas of acute need such as infrastructure, affordable housing, and early childhood care. In addition, for that matter, the public sector could **increase the job yield of such public investments** by limiting the hours of individual jobs and maximizing leave and vacations. Through these initiatives government could lead in addressing crucially important needs while maximizing employment at a time of displacement and adjustment.

EMBRACE TRANSFORMATIVE TECHNOLOGY TO POWER GROWTH

Policymakers in the automation era must also 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—and maintaining the demand for work. As is well-known, high productivity firms generate more output per worker, which in turn allows them to reduce prices, increase market share, and pay better salaries. But beyond that are "productivity effects" of automation discussed by Acemoglu and Restrepo.[48] The productivity effect—resulting from the cost savings and output gains generated by automation—increases the 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.

Therefore, 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.[49] Each of these call for aggressive "bottom-up" strategy-setting and implementation 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 momentum 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 that technology develops effectively and humanely. 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.[50]

Increasing the existing 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.[51] 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.[52] 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 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 startups grow to become global leaders.[53] Finally, it aims to generate more Masters and PhD graduates in machine and deep learning than anywhere else in the world.[54]

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 the private industry.[55] 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.[56]

In sum, the U.S. 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. But the nation and its workers will need more than just a sufficient rate of job creation to offset job destruction that is certain.

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 jobs where 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 deep-set 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. Five strategies for companies, educational institutions, and governments appear urgent to support this change:

- 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 will be to **increase the prevalence of employer-led training**.

While conventional wisdom says that employees, not companies, are the primary beneficiaries of training, a variety of empirical studies have shown that firms frequently recapture the costs of training workers, in particular through increased worker productivity.[57] Employer-led trainings can improve firm output, enhance workers' career prospects, and help companies fill emerging critical needs.[58] Unfortunately, businesses today are less likely than in the past to offer access to on-the-job training or financial support for upskilling.[59]

Likewise, a well-structured program that builds time for training into workers' shifts can help alleviate many of the barriers that workers face.[60] In this regard, more firms should leverage the emergence of new models, such as unbundled online courses, that allow firms and workers to construct curricula to target the skills that they deem most relevant.[61]

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 in this respect, rapid learning in concentrated disaggregated formats will play a growing role. To better facilitate this shift, businesses, educational institutions, governments, and nonprofit 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, focused new collaborations in diverse industry sectors will 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 a 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.[62] These efforts are running in parallel to federal efforts to benchmark new educational funding models, including for accelerated learning.[63] 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 nonprofit group of coding schools based in St. Louis, helps firms in need of "mid-tech" workers to 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.[64] This model not only takes the cost burden off individual workers, but also facilitates stronger training-to-employment pipelines. While this model may work less well for training hard-core developers, it has shown success for retraining incumbent workers and for enabling access for underrepresented candidates. Government agencies should explore how best to leverage this "no charge" 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] 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]

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. For that reason, policymakers should work to not only combat the decline in employer-sponsored training but also to help workers finance their own skills development.

Although firms frequently recapture the costs of training workers, companies remain hesitant to invest, leading to suboptimal training investment throughout the economy.[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] 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]

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, policyakers 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' ongoing 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] 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 should make direct contributions to the accounts of low-income workers.[71] Beyond LiLAs, another way to help workers finance their own skills 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]

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] 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] 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. Another important complement to this will be to encourage tech minors for all students, regardless of field of study.[75] But simple exposure to digital skills will not be enough to prevent attrition. Colleges and universities must also **overhaul curricula in computer science and related fields** to increase real-world content.[76] In this regard, expanded course offerings in hardcore 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]

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]

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] 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]

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] As a result, these groups have a low presence in key tech occupations.[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]

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] 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] 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]

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 with enhanced cognitive and interpersonal skills will need to start, for that matter, even before a child begins kindergarten. More states and municipalities should **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] 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 three to four had access to pre-school in the U.S., and access to early childhood education varied along racial and socioeconomic lines, with minority and low-income children at a significant disadvantage.[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] This is going to require a new, more rigorous focus on the "soft" or "human" skills mentioned above.[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] 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] 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 an AI-dominated 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 heavily rearranged or 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 them to adjust—to learn about a new occupation and/or industry and 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] 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] While the technologies affecting 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 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] 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] However, not every displaced worker can access WIOA services.[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] 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] Now it is time to build it.

The first component of a Universal Adjustment Benefit—not to be confused with a Universal Basic Income—should be the creation 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] 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]

The next piece of a Universal Adjustment Benefit would 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] For comparison, over half of workers enrolled in TAA received training services.[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] For some workers, the marginal pay difference between a new job and federal disability programs may not be that much.[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]

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] 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]

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] Policymakers should therefore **increase funding for active labor market policies** and index future appropriations to the growth of the labor force to prevent the erosion of per capita funding. In addition to investing more in policies that actively connect workers to jobs, the nation should 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] The length of UI benefits also varies, with some states offering as few as 12 weeks.[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] 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 job 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 employee to find a job of their own volition.[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] Workers may receive benefits for up to 24 months in any three-year period.[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]

So how does flexicurity hold up? Some 20 percent of the Danish labor force changes jobs in any given year.[117] Despite this, the Danish unemployment rate never broken 8 percent during the Great Recession, compared to an EU-wide unemployment rate of 10.9 percent at its peak.[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] 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] Meanwhile, Denmark ranks highly on global rankings of entrepreneurship, placing sixth out of 137 countries in the 2018 Global Entrepreneurship Index (the U.S. ranked first).[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]

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 their skills may be more valuable. TAA is again an exception, providing workers a modest 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] 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]

Bundle all of these components together and the U.S. will have assembled a very respectable Universal Adjustment Benefit that would go a long way towards making automation-driven disruption tolerable for all.

MAXIMIZE HIRING THROUGH A SUBSIDIZED EMPLOYMENT PROGRAM

At the same time, adjustment will go better if jobs are plentiful (as noted earlier)—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] 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] 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]

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 take over more work 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. Still others will 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 essential, ready-to-go counterbalance 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]

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] 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] 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 refundable 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] To combat this, policymakers should **create a universal wage insurance program for displaced workers**. This might also become part of a Universal Basic Adjustment package. In any event, 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]

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] 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] 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 deficient 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 software, seasonal demand, or other factors. All of which argues for a stronger, more portable safety net as the AI era progresses.[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] 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] 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] Program assessments have shown an employee adoption 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] Furthermore, surveys conducted by the AARP indicate that over 80 percent of Oregonians support the program on a bipartisan basis.[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] 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 Affordable Care Act coverage gains,** which are especially important for those with tenuous work arrangements. 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] 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]

- Workers own their benefits (i.e. they are not tied to a specific job or company).
- Companies contribute 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 technology like scheduling software has 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] This has led to paycheck uncertainty for a significant portion of American workers, with individuals facing wide swings in their monthly income.[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]

The general point, in any event, 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

Finally, any comprehensive adjustment strategy for the AI era needs also to address the resilience of hard-hit communities. That's because, as reported earlier, individuals' work lives are inextricably shaped by their local labor markets, which vary significantly in how they are being affected by automation.

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] 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] 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] Such programs have had, and can play, a useful role in helping communities adjust to disruptions.[150]

With that said, though, 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] Nor are any of these programs specifically oriented to addressing the kind of worker and community dislocation that will 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] In this regard, 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] 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]

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] Empirical studies show that such employer-specific training programs are an effective way to increase worker productivity, employment, and earnings.[156]

Likewise, the Skillful State Network and Playbook indicates the steps regions must take to reorient their workforce toward in-demand skills.[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, articulated 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.

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] 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] 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] 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] However, these programs' modest scale and disjointed coordination limits their impact. In order to improve effectiveness, a more robust national strategy will almost certainly will 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] Placing federal or state assets in such places—in conjunction with efforts to spark entrepreneurship by streamlining regulations—could help.[163] So could explicit regional catch-up programs.[164]

To be sure, the tendency of U.S. effort 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. 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 larger surrounding vicinity.[165]

DEFENSE ADJUSTMENT PROGRAMS

The Department of Defense (DOD) operates a number of programs that amount to both precedents and workable models for pro-active regional adjustment. And for good reason: The 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, in that sense, 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 help with facilitating the exchange of best practices among communities.[166]

According to a 2013 report by the Government Accountability Office (GAO), 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]

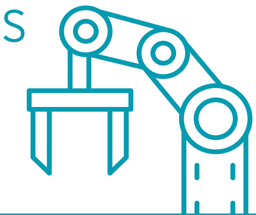
Similarly, the widely-discussed Opportunity Zones program created by the Tax Cuts and Jobs Act of 2017 may help some states and investors **target investment to boost labor demand** in struggling places. As with other place-sensitive efforts, targeted investments should be coupled with shrewdly attuned 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]

FIGURE 12

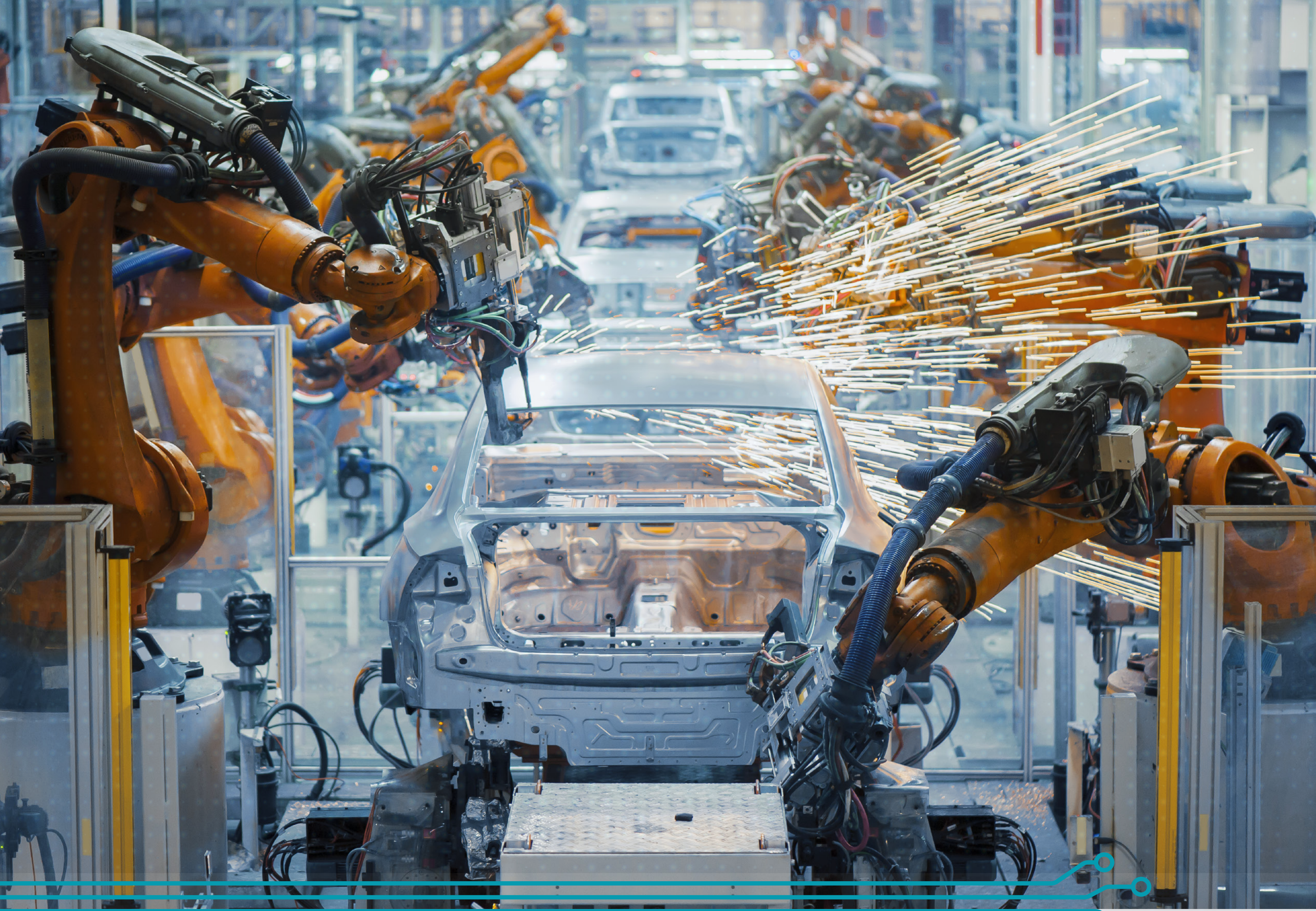
Five policy strategies for adjusting to automation

FIVE POLICY STRATEGIES FOR ADJUSTING TO AUTOMATION



Embrace growth and technology
Run a full-employment economy, both nationally and regionally
Embrace transformative technology to power growth
Promote a constant learning mindset
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
Facilitate smoother adjustment
Create a Universal Adjustment Benefit to support all displaced workers
Maximize hiring through a subsidized employment program
Reduce hardships for workers who are struggling
Reform and expand income supports for workers in low-paying jobs
Reduce financial volatility for workers in low-wage jobs
Mitigate harsh local impacts
Future-proof vulnerable regional economies
Expand support for community adjustment

Source: Metropolitan Policy Program at Brookings



6. CONCLUSION

AI and automation will likely have many positive impacts on the U.S. economy, despite the uncertainty and disquiet they are currently engendering. The trick is going to be to recall as a nation that technology change doesn't "just happen" but that it can be shaped.

On the upside, societal efficiency gains and the paradoxical boons of job creation associated with the "productivity effect" each seem possible, with each bringing substantial benefits to workers, firms, industries, and regions.

Yet, the preceding report has almost certainly underplayed such benefits given its inability to "count" potential "new" jobs. In this respect, if the past is prologue, the demand for new work could be so significant as to offset much of the coming disruption. In this vein, the challenge for the nation is to avoid fear and embrace change while making the most of it.

However, the past might *not* be prologue, given the unique nature of AI. After all, even if AI's rollout does recapitulate some of the economic boons of IT-period automation, the earlier experience is not necessarily reassuring given the economic traumas of the period.

While IT era automation has had many positive impacts on the U.S. economy, it contributed to significant labor market disruptions and a job quality crisis centered on the hollowing out of the wage distribution. Those impacts—exacerbated by weak policy responses—have likely contributed to the social and political crises of the current decade. To the extent those negative impacts and policy derelictions foreshadow the coming years the AI era could be rough.

However, the next few decades need not recapitulate the last few. In fact, the nation can learn from the IT era. And here it is clear that a deliberate, coordinated adjustment stance that enlists federal, state, and local policymakers, business, educators, and civil society has the power to greatly improve the AI era by maximizing the productivity it may bring while mitigating its most negative labor market impacts. In this vein, the nation needs to commit to deep-set 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. If the nation can commit to its people in this way, a future full of machines will seem much more tolerable.

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).

2. David Autor, Frank Levy, and Richard Murnane "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics (2003).*

3. David Autor, "The 'task approach' to labor markets: an overview." *Journal of Labour Market Research* (2013).

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).

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).

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).

7. McKinsey Global Institute. "AI, Automation, and the Future of Work: Ten Things to Solve For." (San Francisco: 2018).

8. 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).

9. See Bessen, *Learning by Doing* and "Automation and Jobs."

10. See Acemoglu and Restrepo, "The Race Between Man and Machine."

11. Ibid.

12. David Autor, "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* (2015b).

13. Daron Acemoglu and Pascual Restrepo, "Artificial Intelligence, Automation, and Work" in Ajay Agarwal, Avid Goldberg, and Joshua Gans, eds., *Economics of Artificial Intelligence.*

14. See Bessen, *Learning by Doing* and "Automation and Jobs."

15. Ibid.

16. Ibid.

17. 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).

18. See Autor and Dorn (2013) and Autor (2015b).

19. See https://occupationalinfo.org/

20. James Manyika and others, "A Future that Works: Automation, Employment, and Productivity." (San Francisco: McKinsey Global Institute, 2017).

21. 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.

22. 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.

23. 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.

24. 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).

25. See Alexandra Spitz-Oener, "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure," *Journal of Labor Economics*.

26. See Acemoglu and Restrepo, "The Race Between Man and Machine."

27. 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).

28. 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).

29. 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).

30. 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).

31. 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).

32. 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).

33. We ran a nonlinear least-squares estimation of the exponential function

Manufacturing employment share in 1980 = $b_0 * b_1$ (Routine employment share in 1980)

The regression yielded an estimate of 707.85 for b_0 and 0.033 for b_1, both of which were highly significant ($p < 0.01$, $R^2 = 0.867$).

34. Muro and others, "Digitalization and the American Workforce".

35. 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."

36. 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.

37. 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).

38. David Autor and Anna Salomons. 2017. "Does Productivity Growth Threaten Employment?" Working paper.

39. See Ross Devol "Perspectives on Definining the American Heartland," (Bentonville, AR: Walton Family Foundation, 2018).

40. Muro and others, "Digitalization and the American Workforce"

41. 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.

42. 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.

43. 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).

44. 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).

45. 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*.

46. Atkinson, "Technological Innovation, Employment, and Workforce Adjustment Policies."

47. Bivins, "Recommendations for Creating Jobs and Economic Security in the U.S."

48. Daron Acemoglu and Pascual Restrepo, "Artificial Intelligence, Automation, and Work."

49. 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).

50. 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.

51. 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).

52. See National Science and Technology Council, "The National Artificial Intelligence Research and Development Strategic Plan."

53. See https://vectorinstitute.ai/about/#visionmission.

54. Mandy Kovacs, "Toronto's Vector Institute expands its AI mission as it finishes assembling team," *IT World Canada*, December 11, 2017.

55. Ibid.

56. See https://www.cifar.ca/ai/pan-canadian-artificial-intelligence-strategy.

57. 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.

58. 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."

59. "Economic Report of the President Together with the Annual Report of the Council of Economic Advisers," (Council of Economic Advisers, 2015).

60. 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.

61. 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).

62. For example, Oregon, in partnership with for-profit coding school Treehouse and the nonprofit 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_%20 2016-02-25.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.

63. 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/.

64. Interview with Jeffrey Mazur; see also https://www.launchcode.org.

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.

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).

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."

68. Alastair Fitzpayne and Ethan Pollack, "Worker Training Tax Credit: Promoting Employer Investments in the Workforce" (Washington: The Aspen Institute, 2017). See also "Establish a Human Development Tax Credit," focused on states and forthcoming from Brookings.

69. Ibid.

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73. Muro and others, "Digitalization and the American Workforce."

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84. Auon, *Robot-Proof*.

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Tough, *Helping Children Succeed: What Works and Why* (Boston: Houghton Mifflin, 2016).

93. Daron Acemoglu and Pascual Restrepo, "Artificial Intelligence, Automation and Work" NBER Working Paper No. 24196.

94. Edward Alden, *Failure to Adjust: How Americans Got Left Behind in the Global Economy* (Lanham, Md.: Roman & Littlefield, 2017).

95. For the official Bureau of Labor Statistics definition of displaced workers, see: https://www.bls.gov/news.release/disp.tn.htm

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).

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98. See Mark Muro and Joseph Parilla, "Maladjusted: It's time to reimagine economic 'adjustment' programs," *The Avenue*, January 10, 2017.

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.

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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).

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140. See "2018 Survey of Oregonians: OregonSaves Program," https://www.aarp.org/research/topics/economics/info-2018/oregon-retirement-savings.html

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.

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).

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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/.

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/.

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165. See Hendrickson, Muro, and Galston, "Countering the geography of Discontent."

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/.

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APPENDICES

APPENDIX A

Automation potential, U.S. states

Rank	State	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
1	Indiana	48.7%	35.2%	35.8%	29.0%
2	Kentucky	48.4%	35.7%	35.6%	28.7%
3	South Dakota	48.3%	35.7%	36.2%	28.1%
4	Iowa	48.0%	36.5%	35.6%	27.9%
5	Nevada	48.0%	33.8%	38.8%	27.4%
6	Arkansas	48.0%	36.4%	35.6%	28.0%
7	Alabama	47.9%	35.5%	37.2%	27.3%
8	Wyoming	47.8%	34.7%	38.8%	26.6%
9	Mississippi	47.7%	36.2%	36.7%	27.0%
10	Wisconsin	47.5%	38.1%	34.7%	27.2%
11	Nebraska	47.5%	36.6%	36.8%	26.6%
12	Tennessee	47.3%	36.2%	36.8%	27.0%
13	Ohio	47.2%	37.8%	34.4%	27.8%
14	Montana	47.0%	36.1%	38.9%	25.0%
15	Oklahoma	46.9%	36.7%	37.5%	25.8%
16	West Virginia	46.9%	37.4%	36.9%	25.7%
17	Kansas	46.8%	37.8%	36.3%	25.8%
18	North Carolina	46.7%	38.2%	35.8%	26.1%
19	North Dakota	46.7%	36.6%	37.5%	25.9%
20	South Carolina	46.6%	37.3%	37.4%	25.3%
21	Michigan	46.5%	38.4%	35.9%	25.6%
22	Missouri	46.5%	38.1%	36.4%	25.5%
23	Maine	46.5%	38.3%	36.3%	25.4%
24	Louisiana	46.5%	37.1%	37.8%	25.0%
25	Texas	46.5%	38.3%	36.2%	25.5%
26	Idaho	46.4%	37.2%	37.8%	25.0%
27	Florida	46.3%	36.7%	38.8%	24.5%
28	New Hampshire	46.1%	37.8%	37.6%	24.6%
29	Oregon	46.1%	39.2%	35.6%	25.2%
30	Rhode Island	46.0%	39.4%	35.8%	24.8%

Rank	State	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
31	Pennsylvania	45.9%	39.8%	35.0%	25.3%
32	Alaska	45.9%	38.9%	36.3%	24.8%
33	Hawaii	45.8%	38.2%	37.0%	24.8%
34	Georgia	45.8%	39.6%	34.8%	25.6%
35	Utah	45.6%	39.1%	36.7%	24.2%
36	Delaware	45.6%	39.0%	36.1%	24.9%
37	Illinois	45.6%	40.6%	33.7%	25.7%
38	California	45.2%	39.9%	36.0%	24.2%
39	Vermont	45.1%	40.7%	35.0%	24.3%
40	Minnesota	45.0%	41.6%	33.7%	24.7%
41	Arizona	45.0%	39.8%	37.2%	23.0%
42	Washington	44.9%	40.2%	35.8%	24.0%
43	Colorado	44.4%	40.8%	36.4%	22.8%
44	New Mexico	44.3%	41.1%	36.8%	22.1%
45	New Jersey	44.1%	41.4%	35.3%	23.3%
46	Virginia	44.0%	41.8%	35.5%	22.7%
47	Connecticut	43.5%	43.0%	35.0%	22.0%
48	Maryland	43.2%	42.3%	37.3%	20.4%
49	Massachusetts	42.9%	43.9%	34.8%	21.3%
50	New York	42.4%	44.5%	35.2%	20.3%

Note: Averages weighted by occupational employment share. Automation potential refers to the share of tasks in an occupation that could be automated with current technologies. "Low risk" jobs are those for which over 30 percent of tasks or less are potentially automatable, "Medium" those with between 30 and 70 percent of tasks automatable, and "High" those with over 70 percent of tasks automatable

Source: Brookings analysis of BLS, Census, EMSI, Moody's, and McKinsey data

Automation potential, top 100 U.S. metros

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
1	Toledo, OH	49.0%	35.1%	35.2%	29.7%
2	Greensboro-High Point, NC	48.5%	36.1%	34.6%	29.4%
3	Lakeland-Winter Haven, FL	48.5%	34.5%	36.6%	28.9%
4	Stockton-Lodi, CA	48.3%	34.5%	36.8%	28.7%
5	Las Vegas-Henderson-Paradise, NV	48.2%	33.1%	39.3%	27.6%
6	Winston-Salem, NC	48.1%	37.7%	34.1%	28.2%
7	Grand Rapids-Wyoming, MI	48.0%	37.2%	34.6%	28.3%
8	Louisville/Jefferson County, KY-IN	47.9%	36.6%	34.8%	28.6%
9	Scranton--Wilkes-Barre--Hazleton, PA	47.8%	37.6%	34.1%	28.3%
10	Fresno, CA	47.8%	33.6%	41.3%	25.1%
11	Cape Coral-Fort Myers, FL	47.7%	32.3%	42.5%	25.2%
12	Deltona-Daytona Beach-Ormond Beach, FL	47.6%	33.9%	41.0%	25.2%
13	Riverside-San Bernardino-Ontario, CA	47.6%	36.1%	35.7%	28.2%
14	Chattanooga, TN-GA	47.5%	36.4%	36.9%	26.7%
15	Wichita, KS	47.5%	36.1%	37.6%	26.3%
16	El Paso, TX	47.4%	37.8%	36.4%	25.8%
17	Tulsa, OK	47.3%	36.0%	37.6%	26.4%
18	Greenville-Anderson-Mauldin, SC	47.2%	37.2%	37.0%	25.8%
19	Akron, OH	47.1%	38.2%	34.1%	27.7%
20	Bakersfield, CA	46.9%	32.5%	44.4%	23.2%
21	Knoxville, TN	46.8%	36.6%	37.6%	25.8%
22	Cincinnati, OH-KY-IN	46.8%	38.3%	34.3%	27.3%
23	Ogden-Clearfield, UT	46.7%	37.2%	36.6%	26.1%
24	North Port-Sarasota-Bradenton, FL	46.7%	34.4%	41.2%	24.4%
25	Allentown-Bethlehem-Easton, PA-NJ	46.6%	38.7%	35.0%	26.3%
26	Oxnard-Thousand Oaks-Ventura, CA	46.6%	36.4%	38.8%	24.9%
27	Cleveland-Elyria, OH	46.5%	38.6%	34.9%	26.5%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
28	Nashville-Davidson--Murfreesboro--Franklin, TN	46.5%	37.4%	36.8%	25.8%
29	Dallas-Fort Worth-Arlington, TX	46.5%	38.4%	35.5%	26.1%
30	New Orleans-Metairie, LA	46.4%	37.6%	37.5%	24.9%
31	Houston-The Woodlands-Sugar Land, TX	46.3%	38.4%	36.0%	25.5%
32	Orlando-Kissimmee-Sanford, FL	46.3%	36.4%	38.8%	24.8%
33	Birmingham-Hoover, AL	46.3%	37.9%	37.1%	25.0%
34	Memphis, TN-MS-AR	46.3%	37.6%	35.3%	27.0%
35	Miami-Fort Lauderdale-West Palm Beach, FL	46.2%	36.8%	38.9%	24.4%
36	Spokane-Spokane Valley, WA	46.2%	39.0%	35.9%	25.1%
37	Jacksonville, FL	46.1%	37.8%	36.7%	25.5%
38	Dayton, OH	46.1%	40.1%	33.1%	26.8%
39	Providence-Warwick, RI-MA	46.1%	38.9%	35.8%	25.3%
40	Omaha-Council Bluffs, NE-IA	46.1%	38.6%	36.4%	25.0%
41	San Antonio-New Braunfels, TX	46.0%	39.4%	36.2%	24.4%
42	Augusta-Richmond County, GA-SC	46.0%	38.8%	37.3%	23.9%
43	Pittsburgh, PA	45.9%	39.6%	35.5%	24.9%
44	Indianapolis-Carmel-Anderson, IN	45.9%	39.1%	34.8%	26.1%
45	Baton Rouge, LA	45.9%	37.0%	39.2%	23.8%
46	Tampa-St. Petersburg-Clearwater, FL	45.9%	38.1%	37.9%	24.0%
47	Oklahoma City, OK	45.8%	38.4%	37.1%	24.5%
48	St. Louis, MO-IL	45.7%	39.2%	36.4%	24.4%
49	Charlotte-Concord-Gastonia, NC-SC	45.7%	39.3%	35.0%	25.7%
50	Buffalo-Cheektowaga-Niagara Falls, NY	45.7%	39.7%	36.2%	24.0%
51	Charleston-North Charleston, SC	45.7%	39.0%	37.5%	23.5%
52	Syracuse, NY	45.6%	40.8%	35.1%	24.1%
53	Los Angeles-Long Beach-Anaheim, CA	45.6%	40.0%	34.6%	25.4%
54	Virginia Beach-Norfolk-Newport News, VA-NC	45.5%	38.6%	37.5%	23.9%
55	Palm Bay-Melbourne-Titusville, FL	45.5%	38.5%	37.7%	23.8%
56	Milwaukee-Waukesha-West Allis, WI	45.5%	41.8%	33.6%	24.6%
57	Detroit-Warren-Dearborn, MI	45.4%	39.9%	35.4%	24.7%
58	Chicago-Naperville-Elgin, IL-IN-WI	45.3%	41.0%	33.4%	25.6%
59	Kansas City, MO-KS	45.2%	40.2%	35.6%	24.2%
60	Provo-Orem, UT	45.1%	39.9%	37.9%	22.2%
61	Harrisburg-Carlisle, PA	45.1%	41.9%	32.7%	25.5%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
62	Little Rock-North Little Rock-Conway, AR	45.1%	40.0%	36.3%	23.6%
63	Urban Honolulu, HI	45.1%	39.6%	36.4%	24.0%
64	San Diego-Carlsbad, CA	45.0%	40.1%	36.3%	23.6%
65	Columbia, SC	45.0%	39.5%	37.4%	23.1%
66	Portland-Vancouver-Hillsboro, OR-WA	45.0%	41.2%	34.4%	24.4%
67	Jackson, MS	44.8%	41.1%	36.2%	22.7%
68	Phoenix-Mesa-Scottsdale, AZ	44.8%	40.2%	36.6%	23.2%
69	Boise City, ID	44.8%	40.3%	36.5%	23.3%
70	Columbus, OH	44.7%	41.9%	33.3%	24.8%
71	Tucson, AZ	44.7%	41.0%	36.9%	22.0%
72	Atlanta-Sandy Springs-Roswell, GA	44.7%	41.3%	34.1%	24.6%
73	Salt Lake City, UT	44.6%	41.0%	35.7%	23.3%
74	Richmond, VA	44.6%	40.6%	36.1%	23.3%
75	Rochester, NY	44.5%	42.1%	35.5%	22.4%
76	Des Moines-West Des Moines, IA	44.5%	41.6%	34.3%	24.0%
77	Worcester, MA-CT	44.4%	42.1%	34.4%	23.5%
78	Austin-Round Rock, TX	44.3%	40.8%	37.4%	21.8%
79	McAllen-Edinburg-Mission, TX	44.3%	44.3%	32.5%	23.2%
80	New Haven-Milford, CT	44.2%	42.9%	35.0%	22.1%
81	Madison, WI	44.0%	43.7%	34.1%	22.2%
82	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	43.9%	42.4%	35.1%	22.5%
83	Minneapolis-St. Paul-Bloomington, MN-WI	43.9%	43.6%	32.9%	23.5%
84	Sacramento--Roseville--Arden-Arcade, CA	43.8%	41.8%	36.0%	22.3%
85	Springfield, MA	43.7%	43.7%	34.1%	22.2%
86	Colorado Springs, CO	43.6%	42.3%	36.2%	21.6%
87	Seattle-Tacoma-Bellevue, WA	43.6%	43.0%	33.8%	23.2%
88	Denver-Aurora-Lakewood, CO	43.6%	42.3%	35.4%	22.3%
89	Hartford-West Hartford-East Hartford, CT	43.5%	43.2%	34.8%	22.0%
90	Baltimore-Columbia-Towson, MD	43.4%	41.9%	37.7%	20.4%
91	Raleigh, NC	43.3%	42.0%	36.5%	21.5%
92	Albuquerque, NM	43.3%	42.9%	36.2%	20.9%
93	Albany-Schenectady-Troy, NY	43.0%	43.5%	36.4%	20.1%
94	San Francisco-Oakland-Hayward, CA	42.8%	43.8%	34.3%	21.8%
95	Bridgeport-Stamford-Norwalk, CT	42.6%	43.7%	35.1%	21.1%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
96	Boston-Cambridge-Newton, MA-NH	42.6%	44.3%	34.8%	20.9%
97	Durham-Chapel Hill, NC	42.4%	46.9%	33.8%	19.3%
98	New York-Newark-Jersey City, NY-NJ-PA	42.2%	44.6%	34.9%	20.5%
99	San Jose-Sunnyvale-Santa Clara, CA	40.4%	48.1%	33.3%	18.6%
100	Washington-Arlington-Alexandria, DC-VA-MD-WV	39.8%	49.0%	33.2%	17.7%

Note: Averages weighted by occupational employment share. Automation potential refers to the share of tasks in an occupation that could be automated with current technologies. "Low risk" jobs are those for which over 30 percent of tasks or less are potentially automatable, "Medium" those with between 30 and 70 percent of tasks automatable, and "High" those with over 70 percent of tasks automatable

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

Automation potential, all U.S. metros

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
1	Dalton, GA	56.0%	28.4%	29.5%	42.1%
2	Kokomo, IN	54.7%	28.8%	33.0%	38.2%
3	Elkhart-Goshen, IN	54.6%	25.9%	38.1%	36.0%
4	Hickory-Lenoir-Morganton, NC	52.6%	30.8%	34.3%	35.0%
5	Grand Island, NE	52.4%	31.6%	34.1%	34.3%
6	Burlington, NC	52.2%	30.3%	37.1%	32.5%
7	Harrisonburg, VA	52.0%	33.1%	33.3%	33.6%
8	Gettysburg, PA	51.6%	31.7%	35.4%	32.9%
9	Sioux City, IA-NE-SD	51.6%	32.0%	35.2%	32.8%
10	Gadsden, AL	51.5%	30.0%	40.5%	29.4%
11	Fort Smith, AR-OK	51.5%	32.7%	34.1%	33.2%
12	Morristown, TN	51.3%	31.2%	36.5%	32.3%
13	Michigan City-La Porte, IN	51.0%	30.3%	38.5%	31.2%
14	Odessa, TX	50.9%	30.8%	37.0%	32.2%
15	Florence-Muscle Shoals, AL	50.9%	30.8%	38.4%	30.8%
16	St. Joseph, MO-KS	50.9%	32.5%	36.2%	31.3%
17	Lima, OH	50.8%	32.1%	35.4%	32.5%
18	Joplin, MO	50.7%	33.7%	33.4%	33.0%
19	Muskegon, MI	50.7%	30.1%	39.0%	31.0%
20	Sheboygan, WI	50.6%	35.3%	32.0%	32.6%
21	Terre Haute, IN	50.6%	32.4%	37.9%	29.7%
22	Auburn-Opelika, AL	50.5%	33.7%	36.7%	29.6%
23	Mansfield, OH	50.4%	32.5%	35.7%	31.7%
24	Columbus, IN	50.3%	33.1%	35.8%	31.1%
25	Gainesville, GA	50.2%	34.1%	34.9%	31.0%
26	Wausau, WI	50.1%	34.9%	33.9%	31.1%
27	Cleveland, TN	50.1%	33.3%	35.5%	31.2%
28	Lebanon, PA	50.1%	35.0%	32.6%	32.4%
29	Greeley, CO	50.1%	33.1%	36.0%	30.9%
30	Lafayette-West Lafayette, IN	50.1%	35.5%	37.7%	26.8%
31	Albany, OR	50.1%	34.2%	34.8%	31.0%
32	Anniston-Oxford-Jacksonville, AL	50.1%	32.6%	37.4%	30.0%
33	Weirton-Steubenville, WV-OH	50.0%	32.6%	37.5%	29.9%
34	Danville, IL	50.0%	34.3%	34.3%	31.4%
35	Lewiston, ID-WA	49.9%	32.1%	39.1%	28.8%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
36	Bowling Green, KY	49.8%	34.6%	36.4%	29.0%
37	Decatur, AL	49.8%	32.8%	36.1%	31.1%
38	Merced, CA	49.7%	32.3%	40.0%	27.8%
39	Canton-Massillon, OH	49.7%	33.9%	35.5%	30.6%
40	Longview, WA	49.7%	33.6%	36.0%	30.4%
41	Decatur, IL	49.6%	34.3%	34.6%	31.0%
42	Modesto, CA	49.6%	32.8%	38.2%	29.0%
43	Tuscaloosa, AL	49.5%	33.5%	39.1%	27.4%
44	Salisbury, MD-DE	49.5%	32.7%	38.8%	28.5%
45	Longview, TX	49.5%	32.9%	37.7%	29.4%
46	Springfield, OH	49.4%	35.5%	32.9%	31.6%
47	St. Cloud, MN	49.4%	35.2%	34.4%	30.4%
48	College Station-Bryan, TX	49.4%	35.1%	40.2%	24.6%
49	Oshkosh-Neenah, WI	49.4%	36.0%	34.1%	29.9%
50	Yakima, WA	49.4%	29.0%	45.1%	25.9%
51	Evansville, IN-KY	49.4%	34.0%	36.0%	30.0%
52	Rocky Mount, NC	49.4%	33.7%	37.4%	28.9%
53	The Villages, FL	49.3%	27.4%	45.5%	27.2%
54	Logan, UT-ID	49.3%	35.6%	36.6%	27.8%
55	Racine, WI	49.3%	35.3%	34.6%	30.1%
56	Owensboro, KY	49.3%	34.2%	36.3%	29.5%
57	Fond du Lac, WI	49.2%	33.5%	38.4%	28.2%
58	Houma-Thibodaux, LA	49.2%	33.0%	36.8%	30.2%
59	Wenatchee, WA	49.2%	29.1%	44.6%	26.4%
60	Waterloo-Cedar Falls, IA	49.1%	35.8%	34.8%	29.4%
61	Goldsboro, NC	49.1%	36.0%	34.6%	29.5%
62	Kingsport-Bristol-Bristol, TN-VA	49.1%	33.6%	37.3%	29.1%
63	Lake Havasu City-Kingman, AZ	49.0%	31.1%	41.9%	27.0%
64	Lancaster, PA	49.0%	34.8%	35.4%	29.8%
65	Toledo, OH	49.0%	35.1%	35.2%	29.7%
66	Monroe, MI	48.9%	33.6%	36.7%	29.7%
67	Fort Wayne, IN	48.9%	34.9%	35.6%	29.5%
68	Williamsport, PA	48.8%	35.8%	36.0%	28.2%
69	Niles-Benton Harbor, MI	48.8%	35.1%	35.9%	29.0%
70	Bay City, MI	48.8%	34.2%	37.5%	28.2%
71	Blacksburg-Christiansburg-Radford, VA	48.8%	37.7%	36.3%	26.0%
72	Texarkana, TX-AR	48.7%	35.4%	36.2%	28.4%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
73	Muncie, IN	48.7%	36.5%	35.7%	27.8%
74	Daphne-Fairhope-Foley, AL	48.7%	31.8%	41.3%	26.9%
75	Green Bay, WI	48.7%	36.5%	34.5%	29.0%
76	Janesville-Beloit, WI	48.7%	35.4%	35.7%	28.9%
77	Vineland-Bridgeton, NJ	48.7%	33.2%	39.2%	27.6%
78	Staunton-Waynesboro, VA	48.7%	35.1%	35.3%	29.6%
79	Rome, GA	48.6%	36.7%	35.6%	27.8%
80	Youngstown-Warren-Boardman, OH-PA	48.6%	33.9%	37.6%	28.5%
81	Appleton, WI	48.6%	35.3%	36.2%	28.5%
82	Hanford-Corcoran, CA	48.6%	29.6%	45.1%	25.3%
83	Amarillo, TX	48.6%	35.4%	37.7%	26.9%
84	Davenport-Moline-Rock Island, IA-IL	48.6%	36.6%	34.2%	29.2%
85	Kankakee, IL	48.6%	35.1%	36.5%	28.4%
86	Greensboro-High Point, NC	48.5%	36.1%	34.6%	29.4%
87	Lakeland-Winter Haven, FL	48.5%	34.5%	36.6%	28.9%
88	Dothan, AL	48.5%	32.9%	39.4%	27.8%
89	Erie, PA	48.5%	37.3%	34.3%	28.4%
90	Mount Vernon-Anacortes, WA	48.4%	32.3%	41.1%	26.6%
91	Saginaw, MI	48.4%	34.3%	38.6%	27.1%
92	Victoria, TX	48.4%	33.6%	39.1%	27.3%
93	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	48.4%	32.8%	40.2%	27.1%
94	Altoona, PA	48.4%	34.8%	37.3%	27.9%
95	Beaumont-Port Arthur, TX	48.4%	34.1%	38.4%	27.5%
96	Medford, OR	48.4%	35.0%	37.3%	27.7%
97	Jacksonville, NC	48.4%	35.5%	36.4%	28.2%
98	Midland, TX	48.4%	33.9%	37.0%	29.1%
99	Stockton-Lodi, CA	48.3%	34.5%	36.8%	28.7%
100	Ocean City, NJ	48.3%	33.0%	40.6%	26.4%
101	York-Hanover, PA	48.3%	35.7%	34.6%	29.7%
102	Lynchburg, VA	48.3%	35.3%	37.1%	27.6%
103	Kahului-Wailuku-Lahaina, HI	48.3%	33.3%	38.6%	28.1%
104	Cape Girardeau, MO-IL	48.3%	35.6%	36.7%	27.6%
105	Jonesboro, AR	48.3%	35.5%	37.1%	27.4%
106	Madera, CA	48.3%	30.6%	46.2%	23.2%
107	Visalia-Porterville, CA	48.3%	29.8%	46.2%	24.0%
108	Dubuque, IA	48.2%	34.7%	37.9%	27.4%
109	Farmington, NM	48.2%	34.0%	38.1%	27.9%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
110	East Stroudsburg, PA	48.2%	33.8%	38.9%	27.3%
111	Mobile, AL	48.2%	35.2%	37.3%	27.5%
112	Sherman-Denison, TX	48.2%	37.2%	35.6%	27.2%
113	Las Vegas-Henderson-Paradise, NV	48.2%	33.1%	39.3%	27.6%
114	Spartanburg, SC	48.2%	34.0%	39.0%	27.0%
115	Jackson, TN	48.2%	35.6%	37.0%	27.4%
116	Springfield, MO	48.1%	35.9%	36.1%	28.0%
117	Clarksville, TN-KY	48.1%	35.9%	36.9%	27.2%
118	Punta Gorda, FL	48.1%	29.7%	45.9%	24.5%
119	Winston-Salem, NC	48.1%	37.7%	34.1%	28.2%
120	Fayetteville-Springdale-Rogers, AR-MO	48.0%	37.5%	33.7%	28.8%
121	Rockford, IL	48.0%	36.3%	35.8%	27.9%
122	Asheville, NC	48.0%	34.7%	38.7%	26.6%
123	Elmira, NY	48.0%	34.2%	39.5%	26.3%
124	Grand Rapids-Wyoming, MI	48.0%	37.2%	34.6%	28.3%
125	Grants Pass, OR	48.0%	36.4%	37.5%	26.1%
126	Waco, TX	48.0%	37.1%	36.7%	26.2%
127	Valdosta, GA	48.0%	35.4%	37.1%	27.5%
128	Bellingham, WA	47.9%	35.3%	38.5%	26.2%
129	Gulfport-Biloxi-Pascagoula, MS	47.9%	33.3%	40.0%	26.7%
130	Carbondale-Marion, IL	47.9%	37.0%	37.7%	25.3%
131	South Bend-Mishawaka, IN-MI	47.9%	38.7%	34.3%	26.9%
132	Ocala, FL	47.9%	33.0%	40.8%	26.2%
133	Hot Springs, AR	47.9%	33.2%	41.0%	25.7%
134	Casper, WY	47.9%	34.1%	39.5%	26.4%
135	Louisville/Jefferson County, KY-IN	47.9%	36.6%	34.8%	28.6%
136	San Angelo, TX	47.9%	36.8%	36.7%	26.5%
137	St. George, UT	47.8%	35.1%	38.6%	26.3%
138	Reading, PA	47.8%	37.0%	34.5%	28.4%
139	Scranton--Wilkes-Barre--Hazleton, PA	47.8%	37.6%	34.1%	28.3%
140	Walla Walla, WA	47.8%	34.1%	41.9%	24.0%
141	Lawton, OK	47.8%	34.6%	40.0%	25.4%
142	Fresno, CA	47.8%	33.6%	41.3%	25.1%
143	Jackson, MI	47.8%	35.7%	38.0%	26.3%
144	La Crosse-Onalaska, WI-MN	47.8%	37.1%	36.4%	26.5%
145	Sebastian-Vero Beach, FL	47.7%	31.9%	43.7%	24.5%
146	Eau Claire, WI	47.7%	37.0%	36.7%	26.3%
147	Rapid City, SD	47.7%	35.0%	38.4%	26.6%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
148	Lake Charles, LA	47.7%	33.2%	41.2%	25.6%
149	Cape Coral-Fort Myers, FL	47.7%	32.3%	42.5%	25.2%
150	Eugene, OR	47.7%	37.1%	36.0%	26.9%
151	Lafayette, LA	47.7%	35.9%	36.9%	27.1%
152	Naples-Immokalee-Marco Island, FL	47.6%	32.7%	41.3%	26.0%
153	Dover, DE	47.6%	35.8%	37.2%	27.0%
154	Deltona-Daytona Beach-Ormond Beach, FL	47.6%	33.9%	41.0%	25.2%
155	Salinas, CA	47.6%	29.0%	49.4%	21.7%
156	Manhattan, KS	47.6%	37.2%	38.0%	24.8%
157	Santa Cruz-Watsonville, CA	47.6%	35.5%	39.2%	25.2%
158	Lubbock, TX	47.6%	37.1%	37.8%	25.1%
159	Riverside-San Bernardino-Ontario, CA	47.6%	36.1%	35.7%	28.2%
160	Flint, MI	47.6%	35.1%	38.8%	26.1%
161	Coeur d'Alene, ID	47.6%	35.6%	38.4%	25.9%
162	Lawrence, KS	47.5%	38.1%	36.6%	25.4%
163	Chattanooga, TN-GA	47.5%	36.4%	36.9%	26.7%
164	Elizabethtown-Fort Knox, KY	47.5%	36.6%	37.4%	26.0%
165	Wichita, KS	47.5%	36.1%	37.6%	26.3%
166	Bloomington, IN	47.4%	38.9%	37.0%	24.2%
167	Chambersburg-Waynesboro, PA	47.4%	36.4%	34.7%	28.9%
168	El Paso, TX	47.4%	37.8%	36.4%	25.8%
169	Lewiston-Auburn, ME	47.4%	37.6%	35.7%	26.7%
170	Billings, MT	47.3%	35.5%	38.1%	26.4%
171	Pine Bluff, AR	47.3%	35.6%	39.4%	24.9%
172	Corpus Christi, TX	47.3%	37.2%	36.1%	26.8%
173	Bloomsburg-Berwick, PA	47.3%	38.9%	35.2%	25.9%
174	Sebring, FL	47.3%	32.6%	44.4%	23.1%
175	Tulsa, OK	47.3%	36.0%	37.6%	26.4%
176	Athens-Clarke County, GA	47.3%	39.6%	35.6%	24.8%
177	Sioux Falls, SD	47.3%	37.8%	34.9%	27.4%
178	Bend-Redmond, OR	47.2%	36.5%	37.2%	26.3%
179	Lexington-Fayette, KY	47.2%	36.5%	38.0%	25.6%
180	Panama City, FL	47.2%	35.2%	38.6%	26.1%
181	Kalamazoo-Portage, MI	47.2%	38.1%	36.1%	25.8%
182	Greenville-Anderson-Mauldin, SC	47.2%	37.2%	37.0%	25.8%
183	Wheeling, WV-OH	47.1%	36.8%	37.0%	26.2%
184	Johnson City, TN	47.1%	38.0%	37.1%	24.9%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
185	Missoula, MT	47.1%	36.4%	38.8%	24.8%
186	Brunswick, GA	47.1%	38.2%	34.5%	27.4%
187	Akron, OH	47.1%	38.2%	34.1%	27.7%
188	Wichita Falls, TX	47.0%	37.1%	37.1%	25.8%
189	Huntington-Ashland, WV-KY-OH	47.0%	37.1%	37.3%	25.6%
190	Parkersburg-Vienna, WV	46.9%	36.3%	37.6%	26.1%
191	Winchester, VA-WV	46.9%	38.9%	34.5%	26.6%
192	Bakersfield, CA	46.9%	32.5%	44.4%	23.2%
193	Napa, CA	46.9%	36.8%	37.4%	25.8%
194	Homosassa Springs, FL	46.9%	32.2%	43.8%	24.0%
195	Hammond, LA	46.9%	37.5%	37.7%	24.7%
196	Abilene, TX	46.9%	37.0%	38.1%	24.9%
197	Prescott, AZ	46.9%	36.3%	38.8%	24.9%
198	Santa Rosa, CA	46.9%	37.1%	36.7%	26.2%
199	Sumter, SC	46.9%	35.9%	39.2%	24.9%
200	Beckley, WV	46.9%	36.0%	39.1%	24.9%
201	Reno, NV	46.8%	37.2%	36.8%	26.0%
202	Iowa City, IA	46.8%	39.6%	36.4%	24.0%
203	Knoxville, TN	46.8%	36.6%	37.6%	25.8%
204	Mankato-North Mankato, MN	46.8%	40.0%	33.6%	26.5%
205	Wilmington, NC	46.8%	36.5%	38.8%	24.7%
206	Cincinnati, OH-KY-IN	46.8%	38.3%	34.3%	27.3%
207	Savannah, GA	46.7%	37.6%	35.8%	26.6%
208	Ogden-Clearfield, UT	46.7%	37.2%	36.6%	26.1%
209	Roanoke, VA	46.7%	36.8%	37.8%	25.4%
210	Greenville, NC	46.7%	38.7%	37.8%	23.5%
211	Hattiesburg, MS	46.7%	38.5%	36.6%	24.9%
212	Cumberland, MD-WV	46.7%	37.5%	38.4%	24.1%
213	North Port-Sarasota-Bradenton, FL	46.7%	34.4%	41.2%	24.4%
214	Grand Forks, ND-MN	46.7%	37.0%	38.6%	24.4%
215	Champaign-Urbana, IL	46.7%	41.4%	34.9%	23.7%
216	Vallejo-Fairfield, CA	46.7%	35.9%	39.2%	24.9%
217	Tyler, TX	46.6%	39.0%	36.1%	24.8%
218	Flagstaff, AZ	46.6%	38.2%	38.4%	23.3%
219	Allentown-Bethlehem-Easton, PA-NJ	46.6%	38.7%	35.0%	26.3%
220	Port St. Lucie, FL	46.6%	35.0%	40.5%	24.6%
221	New Bern, NC	46.6%	37.4%	36.6%	25.9%
222	Florence, SC	46.6%	37.6%	36.8%	25.6%
223	Oxnard-Thousand Oaks-Ventura, CA	46.6%	36.4%	38.8%	24.9%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
224	Portland-South Portland, ME	46.5%	38.4%	36.3%	25.4%
225	Cleveland-Elyria, OH	46.5%	38.6%	34.9%	26.5%
226	Redding, CA	46.5%	37.2%	38.2%	24.5%
227	Chico, CA	46.5%	39.0%	36.4%	24.6%
228	Columbia, MO	46.5%	39.4%	36.6%	24.0%
229	Battle Creek, MI	46.5%	37.4%	38.0%	24.7%
230	Santa Maria-Santa Barbara, CA	46.5%	36.3%	40.4%	23.3%
231	Nashville-Davidson--Murfreesboro--Franklin, TN	46.5%	37.4%	36.8%	25.8%
232	Bangor, ME	46.5%	38.6%	37.1%	24.4%
233	Dallas-Fort Worth-Arlington, TX	46.5%	38.4%	35.5%	26.1%
234	Montgomery, AL	46.4%	36.8%	38.7%	24.5%
235	New Orleans-Metairie, LA	46.4%	37.6%	37.5%	24.9%
236	Hagerstown-Martinsburg, MD-WV	46.4%	37.2%	37.1%	25.7%
237	Lincoln, NE	46.4%	38.7%	36.4%	24.8%
238	Johnstown, PA	46.4%	39.0%	36.1%	24.9%
239	Grand Junction, CO	46.3%	37.1%	38.8%	24.1%
240	Laredo, TX	46.3%	40.1%	34.4%	25.5%
241	Houston-The Woodlands-Sugar Land, TX	46.3%	38.4%	36.0%	25.5%
242	Orlando-Kissimmee-Sanford, FL	46.3%	36.4%	38.8%	24.8%
243	Birmingham-Hoover, AL	46.3%	37.9%	37.1%	25.0%
244	State College, PA	46.3%	40.0%	37.7%	22.3%
245	Killeen-Temple, TX	46.3%	38.0%	37.6%	24.4%
246	San Luis Obispo-Paso Robles-Arroyo Grande, CA	46.3%	37.5%	38.8%	23.8%
247	Memphis, TN-MS-AR	46.3%	37.6%	35.3%	27.0%
248	Atlantic City-Hammonton, NJ	46.3%	34.1%	42.1%	23.8%
249	Fayetteville, NC	46.3%	39.1%	35.7%	25.1%
250	Cheyenne, WY	46.2%	37.3%	37.6%	25.0%
251	Pensacola-Ferry Pass-Brent, FL	46.2%	37.6%	37.6%	24.8%
252	Miami-Fort Lauderdale-West Palm Beach, FL	46.2%	36.8%	38.9%	24.4%
253	Yuba City, CA	46.2%	35.7%	41.0%	23.3%
254	El Centro, CA	46.2%	32.2%	47.3%	20.5%
255	Spokane-Spokane Valley, WA	46.2%	39.0%	35.9%	25.1%
256	Hilton Head Island-Bluffton-Beaufort, SC	46.2%	35.6%	40.1%	24.3%
257	Columbus, GA-AL	46.2%	38.8%	36.4%	24.8%
258	Carson City, NV	46.2%	37.6%	38.2%	24.2%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
259	Crestview-Fort Walton Beach-Destin, FL	46.1%	36.0%	39.5%	24.5%
260	Jacksonville, FL	46.1%	37.8%	36.7%	25.5%
261	Idaho Falls, ID	46.1%	36.6%	39.1%	24.4%
262	Dayton, OH	46.1%	40.1%	33.1%	26.8%
263	Providence-Warwick, RI-MA	46.1%	38.9%	35.8%	25.3%
264	Fairbanks, AK	46.1%	38.3%	38.2%	23.5%
265	Omaha-Council Bluffs, NE-IA	46.1%	38.6%	36.4%	25.0%
266	Macon, GA	46.1%	39.6%	35.7%	24.7%
267	Great Falls, MT	46.1%	37.3%	38.7%	24.0%
268	San Antonio-New Braunfels, TX	46.0%	39.4%	36.2%	24.4%
269	Augusta-Richmond County, GA-SC	46.0%	38.8%	37.3%	23.9%
270	Pueblo, CO	45.9%	37.7%	39.4%	22.9%
271	Kennewick-Richland, WA	45.9%	36.6%	39.5%	23.8%
272	Morgantown, WV	45.9%	41.1%	35.3%	23.6%
273	Fort Collins, CO	45.9%	38.8%	37.9%	23.3%
274	Pittsburgh, PA	45.9%	39.6%	35.5%	24.9%
275	Indianapolis-Carmel-Anderson, IN	45.9%	39.1%	34.8%	26.1%
276	Baton Rouge, LA	45.9%	37.0%	39.2%	23.8%
277	Shreveport-Bossier City, LA	45.9%	38.5%	37.6%	23.9%
278	Tampa-St. Petersburg-Clearwater, FL	45.9%	38.1%	37.9%	24.0%
279	Fargo, ND-MN	45.8%	39.3%	36.3%	24.4%
280	Oklahoma City, OK	45.8%	38.4%	37.1%	24.5%
281	St. Louis, MO-IL	45.7%	39.2%	36.4%	24.4%
282	Monroe, LA	45.7%	40.1%	34.8%	25.1%
283	Charlotte-Concord-Gastonia, NC-SC	45.7%	39.3%	35.0%	25.7%
284	Jefferson City, MO	45.7%	37.5%	40.1%	22.4%
285	Buffalo-Cheektowaga-Niagara Falls, NY	45.7%	39.7%	36.2%	24.0%
286	Charleston-North Charleston, SC	45.7%	39.0%	37.5%	23.5%
287	Syracuse, NY	45.6%	40.8%	35.1%	24.1%
288	Yuma, AZ	45.6%	33.2%	48.2%	18.6%
289	Manchester-Nashua, NH	45.6%	38.2%	38.0%	23.8%
290	Barnstable Town, MA	45.6%	37.7%	37.5%	24.8%
291	Los Angeles-Long Beach-Anaheim, CA	45.6%	40.0%	34.6%	25.4%
292	Hinesville, GA	45.6%	40.8%	33.9%	25.4%
293	Cedar Rapids, IA	45.6%	41.4%	33.0%	25.6%
294	Virginia Beach-Norfolk-Newport News, VA-NC	45.5%	38.6%	37.5%	23.9%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
295	Duluth, MN-WI	45.5%	40.0%	36.2%	23.8%
296	Palm Bay-Melbourne-Titusville, FL	45.5%	38.5%	37.7%	23.8%
297	Salem, OR	45.5%	39.1%	37.6%	23.3%
298	Ames, IA	45.5%	41.7%	34.4%	23.9%
299	Milwaukee-Waukesha-West Allis, WI	45.5%	41.8%	33.6%	24.6%
300	Glens Falls, NY	45.5%	39.2%	37.5%	23.3%
301	Bremerton-Silverdale, WA	45.5%	38.1%	39.0%	22.9%
302	Detroit-Warren-Dearborn, MI	45.4%	39.9%	35.4%	24.7%
303	Kingston, NY	45.4%	39.0%	37.8%	23.2%
304	Albany, GA	45.3%	40.2%	36.0%	23.8%
305	Chicago-Naperville-Elgin, IL-IN-WI	45.3%	41.0%	33.4%	25.6%
306	Utica-Rome, NY	45.2%	41.4%	35.6%	23.0%
307	Watertown-Fort Drum, NY	45.2%	39.3%	37.0%	23.7%
308	Kansas City, MO-KS	45.2%	40.2%	35.6%	24.2%
309	Alexandria, LA	45.1%	39.3%	38.4%	22.4%
310	Corvallis, OR	45.1%	41.2%	37.5%	21.3%
311	Charleston, WV	45.1%	39.5%	37.8%	22.7%
312	Provo-Orem, UT	45.1%	39.9%	37.9%	22.2%
313	Harrisburg-Carlisle, PA	45.1%	41.9%	32.7%	25.5%
314	Little Rock-North Little Rock-Conway, AR	45.1%	40.0%	36.3%	23.6%
315	Urban Honolulu, HI	45.1%	39.6%	36.4%	24.0%
316	Rochester, MN	45.1%	41.8%	35.1%	23.1%
317	Burlington-South Burlington, VT	45.1%	40.4%	35.8%	23.8%
318	San Diego-Carlsbad, CA	45.0%	40.1%	36.3%	23.6%
319	Lansing-East Lansing, MI	45.0%	42.5%	33.6%	23.9%
320	Columbia, SC	45.0%	39.5%	37.4%	23.1%
321	Portland-Vancouver-Hillsboro, OR-WA	45.0%	41.2%	34.4%	24.4%
322	Anchorage, AK	44.9%	40.3%	35.7%	24.0%
323	Norwich-New London, CT	44.9%	38.7%	38.1%	23.2%
324	Warner Robins, GA	44.8%	40.3%	35.5%	24.1%
325	Jackson, MS	44.8%	41.1%	36.2%	22.7%
326	Phoenix-Mesa-Scottsdale, AZ	44.8%	40.2%	36.6%	23.2%
327	Peoria, IL	44.8%	41.3%	34.8%	23.8%
328	Binghamton, NY	44.8%	42.7%	34.5%	22.8%
329	Boise City, ID	44.8%	40.3%	36.5%	23.3%
330	Columbus, OH	44.7%	41.9%	33.3%	24.8%
331	Tucson, AZ	44.7%	41.0%	36.9%	22.0%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
332	Atlanta-Sandy Springs-Roswell, GA	44.7%	41.3%	34.1%	24.6%
333	Topeka, KS	44.6%	40.8%	36.2%	23.0%
334	Salt Lake City, UT	44.6%	41.0%	35.7%	23.3%
335	Richmond, VA	44.6%	40.6%	36.1%	23.3%
336	Gainesville, FL	44.6%	44.1%	35.6%	20.3%
337	Bloomington, IL	44.6%	42.3%	33.8%	23.8%
338	Rochester, NY	44.5%	42.1%	35.5%	22.4%
339	Midland, MI	44.5%	43.2%	33.8%	22.9%
340	Des Moines-West Des Moines, IA	44.5%	41.6%	34.3%	24.0%
341	Ithaca, NY	44.4%	44.6%	35.2%	20.2%
342	Worcester, MA-CT	44.4%	42.1%	34.4%	23.5%
343	Austin-Round Rock, TX	44.3%	40.8%	37.4%	21.8%
344	McAllen-Edinburg-Mission, TX	44.3%	44.3%	32.5%	23.2%
345	Springfield, IL	44.2%	41.8%	36.7%	21.6%
346	Pocatello, ID	44.2%	43.0%	36.4%	20.6%
347	New Haven-Milford, CT	44.2%	42.9%	35.0%	22.1%
348	Ann Arbor, MI	44.1%	45.1%	35.2%	19.6%
349	Madison, WI	44.0%	43.7%	34.1%	22.2%
350	Santa Fe, NM	44.0%	40.3%	38.6%	21.1%
351	Pittsfield, MA	43.9%	41.9%	35.8%	22.3%
352	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	43.9%	42.4%	35.1%	22.5%
353	Minneapolis-St. Paul-Bloomington, MN-WI	43.9%	43.6%	32.9%	23.5%
354	Sacramento--Roseville--Arden-Arcade, CA	43.8%	41.8%	36.0%	22.3%
355	Las Cruces, NM	43.8%	42.8%	36.6%	20.6%
356	Springfield, MA	43.7%	43.7%	34.1%	22.2%
357	Colorado Springs, CO	43.6%	42.3%	36.2%	21.6%
358	Seattle-Tacoma-Bellevue, WA	43.6%	43.0%	33.8%	23.2%
359	Denver-Aurora-Lakewood, CO	43.6%	42.3%	35.4%	22.3%
360	Bismarck, ND	43.6%	40.3%	38.5%	21.2%
361	Olympia-Tumwater, WA	43.6%	43.2%	35.2%	21.6%
362	Hartford-West Hartford-East Hartford, CT	43.5%	43.2%	34.8%	22.0%
363	Charlottesville, VA	43.4%	44.2%	36.1%	19.7%
364	Baltimore-Columbia-Towson, MD	43.4%	41.9%	37.7%	20.4%
365	Raleigh, NC	43.3%	42.0%	36.5%	21.5%
366	Tallahassee, FL	43.3%	43.1%	36.7%	20.3%
367	Albuquerque, NM	43.3%	42.9%	36.2%	20.9%

Rank	Metropolitan area	Average automation potential	Job share by automation risk		
			Low risk	Medium risk	High risk
368	Albany-Schenectady-Troy, NY	43.0%	43.5%	36.4%	20.1%
369	Brownsville-Harlingen, TX	42.9%	47.4%	31.3%	21.3%
370	San Francisco-Oakland-Hayward, CA	42.8%	43.8%	34.3%	21.8%
371	Bridgeport-Stamford-Norwalk, CT	42.6%	43.7%	35.1%	21.1%
372	Sierra Vista-Douglas, AZ	42.6%	44.1%	36.2%	19.7%
373	Boston-Cambridge-Newton, MA-NH	42.6%	44.3%	34.8%	20.9%
374	Boulder, CO	42.5%	45.3%	34.0%	20.8%
375	Durham-Chapel Hill, NC	42.4%	46.9%	33.8%	19.3%
376	Huntsville, AL	42.4%	44.9%	33.7%	21.4%
377	New York-Newark-Jersey City, NY-NJ-PA	42.2%	44.6%	34.9%	20.5%
378	Trenton, NJ	41.0%	47.1%	33.9%	19.0%
379	San Jose-Sunnyvale-Santa Clara, CA	40.4%	48.1%	33.3%	18.6%
380	Washington-Arlington-Alexandria, DC-VA-MD-WV	39.8%	49.0%	33.2%	17.7%
381	California-Lexington Park, MD	39.1%	50.2%	31.3%	18.5%

Note: Averages weighted by occupational employment share. Automation potential refers to the share of tasks in an occupation that could be automated with current technologies. "Low risk" jobs are those for which over 30 percent of tasks or less are potentially automatable, "Medium" those with between 30 and 70 percent of tasks automatable, and "High" those with over 70 percent of tasks automatable.

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

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