



March 2019

WORKFORCE AUTOMATION

Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs

Why GAO Did This Study

Advanced technologies—including artificial intelligence and robotics—are continually changing and emerging. While robots have existed for decades, modern robots may be equipped with learning capabilities that enable them to perform an expansive array of tasks. Advanced technologies are likely to affect the U.S. workforce by enabling firms to automate certain work tasks. Questions exist about how prepared federal agencies are to monitor workforce changes, promote economic growth, and support workers who may be negatively affected by automation.

GAO was asked to examine workforce issues related to the adoption of advanced technologies. This report examines (1) what is known about how the adoption of advanced technologies affects the U.S. workforce; (2) federal efforts to track these effects; (3) considerations that led selected firms to adopt advanced technologies and the risks they faced; and (4) ways technology adoption has affected the workforce at selected firms.

GAO identified available federal workforce data, analyzed the extent to which those data could identify and measure workforce effects due to advanced technologies, reviewed selected research, and analyzed federal data on occupations susceptible to automation. GAO used data from the American Community Survey (2010-2016), the Current Population Survey's Displaced Worker Supplement (2016), and the Occupational Employment Statistics (2017).

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What GAO Found

Although existing federal data provide useful information on the U.S. workforce, they do not identify the causes of shifts in employment. As a result, it is difficult to determine whether changes are due to firms adopting advanced technologies, such as artificial intelligence and robots (see photo), or other unrelated factors. In lieu of such data, GAO analyzed employment trends and characteristics of jobs that selected researchers identified as susceptible to automation, and found that:

- industries with a greater proportion of jobs susceptible to automation were more likely to have experienced growth in tech jobs (i.e., computing, engineering, and mathematics) from 2010 to 2016—possibly an indicator of industries preparing to adopt advanced technologies;
- occupations susceptible to automation and industries with a greater share of these jobs did not experience meaningfully higher job loss rates in this period, though it could be too soon to observe these effects; and
- certain groups, such as workers with no college education and Hispanic workers, tended to hold jobs susceptible to automation in 2016, and thus could be disproportionately affected by changes if they occur.

Example of an Advanced Technology: A Collaborative Robot in the Workplace



Source: A small manufacturer of rubber stamps and embossing seals. © 2018 the stamp manufacturer. | GAO-19-257

The Department of Labor (DOL) has a role in tracking changes in the U.S. workforce, but the data it collects related to the workforce effects of advanced technologies are limited. DOL's Bureau of Labor Statistics (BLS) identifies occupations projected to experience staffing pattern changes and the most significant causes, such as use of robotics, but its efforts are not designed to capture all instances of changes due to advanced technologies. DOL's

GAO met with 16 firms that are using advanced technologies in their operations and seven firms that develop advanced technologies, and interviewed managers and workers, and observed firms' use of technologies. The selected firms varied in size, industry sector, types of technologies used, and geographic location. Findings from discussions with the firms are not generalizable, but provide illustrative examples about the adoption of advanced technologies. GAO interviewed officials from federal agencies, including Commerce and DOL, academic researchers, economists, labor union officials, industry association officials, officials from state economic development associations, and other knowledgeable individuals. GAO also reviewed relevant academic work.

What GAO Recommends

GAO recommends that DOL develop ways to use existing or new data collection efforts to identify and systematically track the workforce effects of advanced technologies. DOL agreed with GAO's recommendation, and plans to identify and recommend data collection options to fill gaps in existing information about how the workplace is affected by new technologies, automation, and artificial intelligence. DOL also stated that it will continue coordinating with the Census Bureau on research activities in this area.

Occupational Information Network program also collects data on tasks and technologies in occupations, such as robotics, but it was not designed to track changes over time. According to BLS, these efforts and other data they collect provide some, but not all, of the information required to identify and systematically track the impact of automation on the workforce. Without comprehensive data that link technological changes to shifts in the workforce, DOL lacks a valuable tool for ensuring that programs it funds to support workers are aligned with local labor market realities, and employers and job seekers need to rely on other sources of information to decide what training to offer or seek.

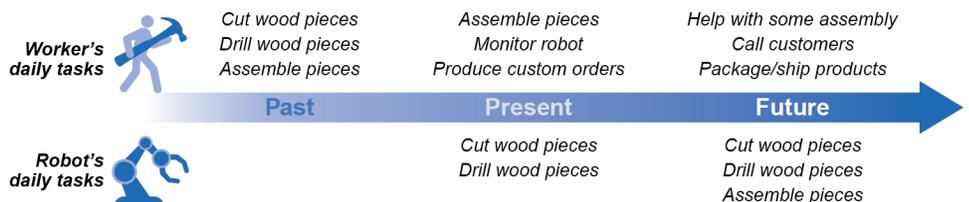
The Department of Commerce's Census Bureau (Census) has started tracking technology adoption and resulting workforce effects in the new Annual Business Survey, which was administered for the first time in June 2018 with significant support from the National Science Foundation. This first survey asked firms about their use of advanced technologies and initial results will be available in late 2019. When the survey is next administered in summer 2019, Census plans to ask additional questions about firms' motivations for adopting technologies and effects the technologies might have on workers. This survey could provide information about the prevalence of technology adoption and workforce changes (e.g., declines in production workers or increases in supervisory workers), but it is not intended to provide information on the magnitude of workforce changes. Also, it remains unclear what limitations, if any, the survey data may have.

According to officials from the 16 firms GAO interviewed, cost savings and other considerations led them to adopt advanced technologies, despite facing certain risks with the new technologies. Officials from these firms typically identified cost savings and improving job or product quality as primary motivations for adopting advanced technologies. For example, an automotive parts manufacturer said the firm adopted robots to reduce costs by using fewer workers. A door manufacturer said the firm installed two robots to lift heavy doors onto a paint line to reduce the number of worker injuries. A rubber stamp manufacturer said acquiring a robot (pictured above) allowed it to purchase and process raw materials instead of buying precut materials. Firm officials also identified risks related to adopting advanced technologies that could affect their return on investment, such as risks related to the reliability of technology and working with new tech developers.

Among the firms GAO met with, officials described various ways technology adoption has affected their workforces. On one hand, officials at many firms said they needed fewer workers in certain positions after adopting technologies. The firms generally redeployed workers to other tasks, and in some cases, reduced the size of their workforces, typically through attrition. For example, a medical center GAO visited adopted autonomous mobile robots to transport linens and waste, among other things, which officials said eliminated 17 positions and shifted workers to other positions. On the other hand, officials at some firms said advanced technologies helped them increase competitiveness and add positions. An appliance manufacturer used advanced technologies to produce more of its own parts instead of relying on suppliers and, as a result, increased the number of production jobs, according to officials. Firm officials also noted that workers' tasks and skills have been changing due to advanced technologies (see figure). Workers who can adapt to new roles may experience positive effects, such as work that is safer, while those who cannot adapt may be negatively affected.

Illustration of Changes to a Worker's Tasks after a Firm Integrates a Robot

How the introduction of a robot might impact the lone production worker at a small stamp manufacturer:



Source: GAO analysis of discussions with officials from a small manufacturer of rubber stamps and embossing seals. | GAO-19-257

View [GAO-19-257](#). For more information, contact Cindy Brown Barnes at (202) 512-7215 or brownbarnesc@gao.gov.

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Abbreviations

ABS	Annual Business Survey
ACS	American Community Survey
AI	Artificial intelligence
BLS	Bureau of Labor Statistics
Census	Census Bureau
Commerce	Department of Commerce
CPS	Current Population Survey
DOL	Department of Labor
ETA	Employment and Training Administration
IFR	International Federation of Robotics
National Academies	National Academies of Sciences, Engineering, and Medicine
NSF	National Science Foundation
O*NET	Occupational Information Network
OES	Occupational Employment Statistics
OSTP	White House Office of Science and Technology Policy

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March 7, 2019

The Honorable Richard E. Neal
Chairman
Committee on Ways and Means
House of Representatives

The Honorable Suzan K. DelBene
House of Representatives

Advanced technologies and artificial intelligence, such as robotics, machine learning, and machine vision, are likely to have significant effects on the U.S. workforce. As firms adopt advanced technologies, the automation of work tasks may change employment and productivity levels and the skills needed in the workforce. Questions exist about how well-equipped federal agencies are to monitor workforce changes in the coming years and respond in ways that encourage economic growth while also supporting workers who may be negatively affected.

You asked us to study the effects of advanced technologies on the U.S. workforce. This report examines 1) what is known about how the adoption of advanced technologies affects the U.S. workforce; 2) selected federal agency efforts to track and monitor the adoption and workforce effects of advanced technologies; 3) considerations that led selected firms to adopt advanced technologies and the risks they faced; and 4) ways technology adoption has affected the workforce at selected firms.

We use “advanced technologies” as a broad term to describe technological drivers of workforce changes, including but not limited to those identified in a recent study by the National Academies of Sciences, Engineering, and Medicine (National Academies): artificial intelligence; machine learning; robotics; autonomous transport; 3D printing; advanced manufacturing; advanced materials; computing power; and internet and cloud technology.¹ The technologies we observed at selected firms could generally be categorized as applications of robotics, machine learning (e.g., machine vision or autonomous navigation), or both. However, not all technologies that may affect the U.S. workforce in the future—through

¹ National Academies of Sciences, Engineering, and Medicine, *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?* (Washington, D.C.: The National Academies Press, 2017).

automation or in other substantial ways—fall into these categories. Our use of the broad term “advanced technologies” leaves open the possibility that new technologies and other areas of focus are likely to emerge.

To analyze what is known about how the adoption of advanced technologies affects the U.S. workforce, we explored the extent to which available federal data could identify and measure these effects. After considering the limitations of available data to link employment trends to technology adoption in a comprehensive way, we used a study by researchers Frey and Osborne that identified occupations susceptible to automation based on the tasks associated with them.² We analyzed these occupations to glean insight about the workforce effects of advanced technology adoption. While different studies attempt to predict what jobs might be automated in the future, we used this study because it is widely cited and its results are structured in a way that allowed us to identify a broadly inclusive group of occupations susceptible to automation. The results of our analyses could be affected by using other studies to the extent they identify different occupations as susceptible to automation. We analyzed the occupations Frey and Osborne identified as susceptible to automation using employment data from the Census Bureau (Census) and the Bureau of Labor Statistics (BLS). Specifically, we used data from the American Community Survey (ACS), 2010-2016; the Current Population Survey’s (CPS) Displaced Worker Supplement, 2016; and the Occupational Employment Statistics (OES) survey, 2017. We analyzed whether the concentration of these occupations in industries is correlated with growth in tech jobs (i.e., jobs in the fields of computing, engineering, and mathematics) or employment declines in those industries, whether job displacements are more common in these occupations than in others, the characteristics of workers who hold jobs in these occupations, and the geographic concentration of jobs in these occupations. For more detail on our data analysis methods, see appendix I.

We also reviewed examples of recent and ongoing studies that attempt to measure workforce effects directly attributable to technology adoption. We identified studies through interviews with knowledgeable individuals and from those included in a recent review of the state of empirical work.³

² Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016). For more information, see appendix I.

³ Manav Raj and Robert Seamans, “AI, Labor, Productivity and the Need for Firm-Level Data” [draft dated 4/15/2018].

Our review of studies was not meant to be comprehensive of the research in this area.

To identify selected federal agencies' current and planned efforts to collect data on and monitor the prevalence and effects of advanced technologies in the economy, we met with the Departments of Labor (DOL) and Commerce (Commerce) as the principal federal agencies responsible for collecting data on the U.S. economy and workforce; the White House Office of Science and Technology Policy (OSTP), which leads interagency science and technology policy-coordination efforts across federal agencies; and the National Science Foundation (NSF), which was involved in the development of the Annual Business Survey.⁴ We interviewed officials and reviewed data and information collected by these agencies. We also reviewed Commerce's new Annual Business Survey questionnaire to consider the potential uses of data being collected by the survey, and analyzed data from DOL's Employment Projections program and Occupational Information Network (O*NET) database to identify information related to the adoption and workforce effects of advanced technologies.⁵

To understand the adoption of advanced technologies by firms and the resulting workforce effects, we met with officials representing 16 firms that are using advanced technologies and a systems integrator who spoke for several of his customer firms. To identify firms to meet with, we consulted a variety of sources, such as researchers, technology developer firms, state economic development associations, and our own research. We limited our focus to firms that had adopted advanced technologies and had experienced workforce effects. Our findings from our discussions with the selected firms are not generalizable, but do provide illustrative examples of how various advanced technologies are being used and how workers have been affected. We selected firms to provide a range of size, industry sector, types of advanced technologies used, and geographic location. For example, of the 16 firms we met with, 10 are manufacturers and 6 are non-manufacturing firms of various types (e.g., a university-

⁴ Identifying and analyzing federal involvement in technology or artificial intelligence (AI) research and development was not within our scope.

⁵ The Annual Business Survey was administered for the first time in summer 2018 and is a joint effort by the Census Bureau and the National Center for Science and Engineering Statistics within the National Science Foundation. For more information about the survey and our methods for analyzing employment projections and the O*NET database, see appendix I.

affiliated medical center and a warehouse for a regional grocery store chain).⁶ When possible, we met with multiple managers and workers, and observed advanced technologies in operation. Topics of discussion with representatives of the firms included motivations for adopting advanced technologies, the integration process, and any resulting workforce effects, such as positions lost and gained as well as changes to workers' tasks.

To obtain varying perspectives to supplement these profiles of firms that use advanced technologies, we also interviewed officials at seven firms that develop advanced technologies (hereafter referred to as developers), two robotics integrator firms that assist client firms with adopting advanced technologies, three industry-based organizations, two unions representing manufacturing workers, and two worker training centers.

For all of the datasets used in our study, we reviewed documentation, interviewed or obtained information from officials responsible for the data, and tested the data for inaccuracies. We determined that the data were sufficiently reliable for the purposes of this report.⁷ In addition, we reviewed relevant federal laws and regulations related to all of the objectives of this study. See appendix I for more detailed information about our scope and methodology.

We conducted this performance audit from October 2017 to March 2019 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our

⁶ We use the term "firm" for simplicity when discussing the technology-using entities we met with. These included single-location firms, production plants of large manufacturers, multinational corporations, a medical center, public sector agencies, and other types. Throughout our report, we provide descriptors for the types of firms we visited, such as a small automotive parts manufacturer or a university-affiliated medical center. For the 10 manufacturing firms, we provide the relative size of the firm and what it produces. For the purposes of our study, we categorize manufacturers as small if they have fewer than 200 employees; medium if they have 200 to 1,000 employees; and large if they have over 1,000 employees, according to officials. For more information about the types of firms we met with, see appendix I.

⁷ Throughout our report, survey-based estimates are reported with their applicable margins of error. Because each survey's sample is only one of a large number of samples that might have been drawn and each sample could have provided different estimates, we express our confidence in the precision of our particular sample's results as the margin of error (i.e., the half width of the 95 percent confidence interval—for example, +/- 7 percentage points). This is the interval that would contain the actual population value for 95 percent of the samples that could have been drawn.

findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Background

Automation, Artificial Intelligence, and Advanced Technologies

Throughout history, new technologies have transformed societies. Many technological advances, ranging from the steam engine to electricity and personal computers, have enhanced productivity and improved societal standards of living. At the same time, many technological advancements have led to increases in automation—modifying processes to become more automatic by reducing human involvement—and corresponding changes in the workforce. For example, researchers have noted that automation has replaced tasks performed by workers and also increased production, creating a greater demand for other types of workers.⁸

Although automation has historically been a labor disrupter in manufacturing and physical work, various researchers have observed that recent progress in fields such as artificial intelligence (AI) and robotics are enabling machines to perform cognitive tasks currently performed by humans.⁹ Artificial intelligence refers to machines and computers that attempt to mimic various aspects of human intelligence, as we have reported.¹⁰ The field of AI can be traced back to the 1950s. Early AI often consisted of expert systems programmed by humans to perform predefined tasks. This form of AI resulted in some degree of productivity gains and remains an active area of development. However, numerous factors, primarily the trends underlying big data (i.e., increased data availability, storage, and processing power), have contributed to rapid

⁸ See for example David Autor, “Why Are There Still So Many Jobs?: The History and Future of Workplace Automation,” *Journal of Economic Perspectives*, vol. 29, no. 3 (2015).

⁹ See for example Jürgen Frohm, et al., “Levels of Automation in Manufacturing.” *Ergonomia - International Journal of Ergonomics and Human Factors*, vol. 30, no. 3 (2008), and National Academies, *Information Technology and the U.S. Workforce* (2017).

¹⁰ There is no single universally accepted definition of AI, but there are differing definitions and taxonomies. For example, one study defines AI as computers or machines that seek to act rationally, think rationally, act like a human, or think like a human; see GAO, *Technology Assessment: Artificial Intelligence Emerging Opportunities, Challenges, and Implications*, [GAO-18-142SP](#) (Washington D.C.: March 28, 2018), and Stuart Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach*, 3rd ed. (NJ: Pearson, 2010).

innovation and accomplishments in AI in recent years. Present-day AI innovation centers more on machine learning, including deep neural network architectures, in which systems are trained against observational or simulated outcomes—applications include language translation and machine vision (i.e., systems that use cameras, radar, or lasers to observe their surroundings or recognize content).¹¹ Industrial robots and robotic machinery are often more comparable to expert systems that are programmed to perform predefined tasks, but they can also incorporate machine learning, such as having machine vision capabilities (e.g., object recognition). Below are some examples of expert system and machine learning applications of artificial intelligence.

Examples of expert system applications of AI:

- software programs that prepare tax filings or schedule logistics; and
- industrial robots that perform predefined or routine tasks, such as lifting, placing, and welding pieces of metal together.

Examples of machine learning applications of AI:

- software that uses a training dataset to “learn” how to read information from a form filled out by a person;
- collaborative robots that can sense when they touch a physical obstruction and shut down to safely work alongside humans;¹²
- industrial robots with machine vision incorporated to identify and pick up specific parts from a collection of randomly strewn pieces; and
- automated guided vehicles that transport materials around a production plant and use cameras and radar to navigate independently and re-route around obstacles.

¹¹ Deep neural networks, a subset of machine-learning algorithms, have been trained to classify images, detect objects, identify people from faces, generate text from speech, translate natural languages, and many other tasks; see [GAO-18-142SP](#).

¹² Collaborative robots are designed for direct interaction with humans within a defined collaborative workspace with certain safety standards required, according to the Robotic Industries Association. Collaborative robots we observed consisted of, among other things, robot arms that could be moved and manipulated by humans to “train” the robots to perform tasks and that could also work on production lines next to and in close proximity with human workers. Officials told us that these collaborative robots would stop immediately if they met an unexpected obstruction, such as bumping a human worker, among other safety precautions.

Advanced technologies, including AI and other technological drivers of workforce changes, are continually progressing and new developments emerge regularly. For example, automated vehicles have varying levels of autonomy.¹³ Similarly, while robots have existed for decades, today's generation of robots may be equipped with machine vision and learning capabilities that enable them to perform a more expansive array of tasks. How, when, or whether technologies progress from development to commercialization (i.e., readiness for adoption), and how, when, or whether firms adopt the technologies is generally dependent on context-specific considerations, which are difficult to predict. To better understand these developments and how they affect the economy, the National Academies report recommended developing three indexes (technology progress index; AI progress index; and organizational change and technology diffusion index) to measure technology progress and the extent of adoption.¹⁴ The study suggested that indexes could be valuable for identifying what fields are advancing rapidly and what benchmarks might indicate the imminence of significant economic impact, as well as tracking and predicting the types of human tasks that can be automated and the impacts of technology adoption by industry. Stanford University's AI Index project is another initiative that aims to track, collate, and visualize data related to artificial intelligence. The data collected by the AI index measure, among other things, volume of AI activity (e.g., published papers, course enrollment, AI-related startups, job openings) and technical performance (e.g., object detection and speech recognition).¹⁵ However, the potential uses and limitations of the data being compiled are yet to be seen, as this initiative is still in its early stages.

¹³ The Department of Transportation has adopted a framework for automated driving developed by the Society of Automotive Engineers International, which categorizes driving automation into six levels from no automation to full automation. For more information, see GAO, *Automated Trucking: Federal Agencies Should Take Additional Steps to Prepare for Potential Workforce Effects*, [GAO-19-161](#) (Washington, D.C.: March 2019).

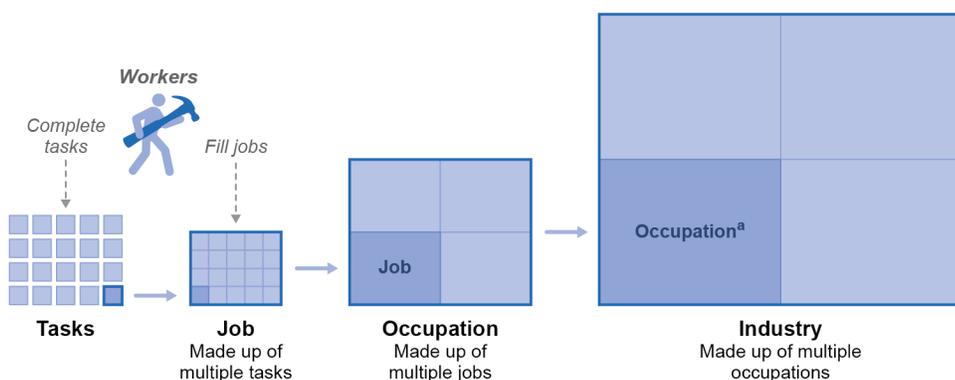
¹⁴ The National Academies report directed its recommendations to federal agencies or other organizations that sponsor research or collect data relevant to technology and the workforce. National Academies, *Information Technology and the U.S. Workforce* (2017).

¹⁵ The AI Index is a part of the Stanford 100 Year Study on AI; see Artificial Intelligence Index, "2017 Annual Report" (2017).

Projected Workforce Effects of Advanced Technologies

While national employment data measure jobs and workers by occupation and industry, the adoption of advanced technologies generally affects specific work tasks, and can materialize in a variety of ways. As shown in figure 1, industries are made up of various occupations, which in turn are formed by a group of jobs. Underlying all, jobs are comprised of a collection of varied work tasks.

Figure 1: The Structure of Employment, from Work Task to Industry



Source: GAO analysis. | GAO-19-257

^aMost occupations are present in multiple industries.

By analyzing tasks within jobs or occupations to determine their susceptibility to automation, a number of studies have developed models to estimate the future workforce effects of advanced technology adoption. The three example studies below each developed similar models, though differences in methods and data sources produced varying conclusions about the number of jobs that may be automated in the future.

- In a 2016 article, researchers Frey and Osborne estimate that 47 percent of total U.S. employment is in occupations that are at high risk of automation over the next decade or two (i.e., by 2030). For example, the authors observe both that industrial robots will be able to perform a wider scope of non-routine manual tasks and that a

substantial share of employment in services, sales, and construction occupations exhibit high probabilities of automation.¹⁶

- A 2017 report by the McKinsey Global Institute estimates that 23 percent of total U.S. work hours could be automated by 2030 or as high as 44 percent under other assumptions.¹⁷ The report predicts that while labor demand will enable some re-employment of displaced workers, up to one-third of the workforce may need to change occupational categories.
- In a 2016 paper, researchers Arntz, Gregory, and Zierahn estimate that 9 percent of all U.S. workers hold jobs that are at high risk of automation.¹⁸ The authors observe that susceptibility to automation is lower for jobs that require cooperating or influencing others.

Studies by Autor and others also develop theoretical models exploring the effects of automation. For example, they noted that while automation can substitute for some tasks, it can also complement others. This can lead to increasing value for tasks that require other attributes like creativity and intuitive judgement. These models hypothesize that automation may have a net positive effect on employment, or at least on employment in certain sectors, which is consistent with historical employment trends. However, researchers have also noted that machine learning may affect different tasks than earlier forms of automation and may be less likely to automate

¹⁶ Frey and Osborne, "The Future of Employment" (2016). Frey and Osborne rely on task data from the Occupational Information Network (O*NET) database and employment data as of 2010; thus, two decades beyond their analysis period is 2030. They identify occupations with a probability of automation that is greater than 0.7 as being at high risk of automation. For more information, see appendix I.

¹⁷ McKinsey Global Institute, *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*, (McKinsey & Company, 2017). The report uses task data from the O*NET database and employment data as of 2014.

¹⁸ Melanie Arntz, Terry Gregory, and Ulrich Zierahn, "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis," *OECD Social, Employment and Migration Working Papers*, no. 189 (Paris: OECD Publishing, 2016). The report uses task data from the 2012 Programme for the International Assessment of Adult Competencies (PIAAC), combined with the work of researchers Frey and Osborne.

low-wage jobs—though low-wage workers may be affected in other ways.¹⁹

Workforce Effects of Advanced Technologies in Broader Context

Although the models discussed above represent ways of identifying jobs that may be affected by the adoption of advanced technologies, they do not provide a model for tracking the current or to-date workforce effects of technology adoption. As the recent National Academies report states, “making forecasts about social phenomena is perilous... [and] doing so with respect to the fast-changing and dynamic area of technology is even more challenging.”²⁰ According to a different project by some of these same experts, several factors unrelated to whether a task or job could be automated contribute to these challenges.²¹ For example, technologies may substitute for human labor in some tasks, but:

- may also complement human labor in other tasks—increasing the demand for, or value of, human labor (e.g., the automation of calculation tasks leading to increased demand for human programmers);
- prices and demand for products may counteract this human labor substitution (e.g., technology reducing the price of air travel, and thus leading to increased demand for flights, and thus increased employment in the aviation industry); and
- firms may redesign operations in response to the substitution in ways that lead to employment increases or decreases that are greater than the direct substitution.

As discussed in the National Academies report and elsewhere, researchers have tried to disentangle workforce effects in various ways,

¹⁹ See for example, Autor, “Why Are There Still So Many Jobs?”, Daron Acemoglu and David Autor, “Skills, Tasks and Technologies: Implications for Employment and Earnings, *Handbook of Labor Economics*, vol. 4b (2011), and Erik Brynjolfsson, Tom Mitchell, and Daniel Rock, “What Can Machines Learn and What Does it Mean for Occupations and the Economy,” *AEA Papers and Proceedings*, vol. 108 (2018).

²⁰ National Academies, *Information Technology and the U.S. Workforce* (2017).

²¹ Erik Brynjolfsson and Tom Mitchell, “What Can Machine Learning Do?: Workforce Implications,” *Science*, vol. 358, no. 6370 (2017).

such as analyzing productivity data to examine workforce trends in the context of other economic factors, such as globalization.²²

As the National Academies report observes, “Predictions that new technologies will make workers largely or almost entirely redundant are as old as technological change itself.... However, predictions of widespread, technologically induced unemployment have not come to pass, at least so far.” Since recovering from the recession of 2007-2009, the economy has recently experienced low unemployment rates—4.0 percent in January 2019—despite continued strides in advanced technologies.²³ However, other indicators have not recovered. For example, the labor force participation rate—the percentage of the population that is either employed or seeking work—declined significantly through the recession and has generally remained at this lower level.²⁴ This may indicate that the post-recession decline in the unemployment rate may over-represent the health of the labor market, according to BLS. Advanced technologies and automation may also affect workers in other ways, beyond potential changes in the workplace, such as by reducing production costs and thus lowering the prices of consumer goods.

²² National Academies, *Information Technology and the U.S. Workforce* (2017). See also for example, Michael Hicks and Srikant Devaraj, Ball State University, Center for Business and Economic Research, “The Myth and the Reality of Manufacturing in America” (2015). The authors estimate that most job loss in manufacturing from 2000 through 2010 was due to productivity increases (i.e., automation and technology advances), as opposed to trade (i.e., globalization).

²³ According to the National Bureau of Economic Research, the 2007-2009 recession began in December 2007 and ended in June 2009. For the unemployment rate in January 2019, see Department of Labor, Bureau of Labor Statistics, *News Release: The Employment Situation – January 2019* (Washington, D.C.: February 2019).

²⁴ A large part of the decline in labor force participation is due to the aging of the population, though the participation rate also declined for younger age groups, according to BLS.

No Comprehensive Data Exist to Link Employment Trends to Advanced Technology Adoption, but Analyses Suggest Relationships

There are currently no comprehensive data on firms' adoption and use of advanced technologies. As a result, researchers have difficulty determining whether changes in the U.S. workforce observed in existing employment data are related to advanced technologies. The National Academies report states that federal household and employer surveys, such as the CPS, ACS, and OES, provide useful information about changes to the occupational mix of the U.S. workforce over time.²⁵ However, these data cannot identify the causes of employment shifts. For example, these data do not identify whether an employment decline in one occupation is due to jobs being replaced as a result of automation, or to other factors unrelated to automation.²⁶ Other federal data, such as the Job Openings and Labor Turnover Survey, provide useful information on employment turnover and opportunities.²⁷ However, although these data are available by industry sector and firm size, the data do not capture reasons for layoffs and discharges, and thus cannot be linked to advanced technologies.

²⁵ National Academies, *Information Technology and the U.S. Workforce* (2017).

²⁶ Due to OES survey design, the occupational employment data collected by BLS are not designed for longitudinal analyses of occupational employment and shifts over time. According to BLS, the agency is considering moving to a design that would allow comparisons over time.

²⁷ According to BLS's February 2019 publication, there were 7.3 million job openings at the end of December 2018, and there were 1.7 million layoffs and discharges that month. Department of Labor, Bureau of Labor Statistics, *News Release: Job Openings and Labor Turnover – December 2018* (Washington, D.C.: February 2019).

Employment Trends and Characteristics of Workers in Jobs Susceptible to Automation

Jobs Susceptible to Automation

Using a model that evaluates tasks within an occupation, Frey and Osborne estimate a probability of automation for 702 occupations. Probabilities range from a 0 percent chance of automation to a 100 percent chance of automation. They ultimately classify occupations with probabilities greater than 70 percent as being at high risk of automation.

For example, Frey and Osborne estimate that healthcare social workers and choreographers have probabilities of automation of 0.4 percent—an extremely low likelihood. On the other hand, they estimate that tax preparers and telemarketers have probabilities of automation of 99 percent—an extremely high likelihood.

In our analyses, we consider the “high-risk” group identified by Frey and Osborne as those occupations susceptible to automation. While there are different studies that attempt to predict what jobs may be automated in the future, we use this study because it is widely cited and because its results are structured to allow us to identify a broad group of occupations to examine.

Source: GAO analysis of Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016). | GAO-19-257

In the absence of comprehensive data that definitively link employment trends to technology adoption, we analyzed occupations that researchers Frey and Osborne identified as being susceptible to automation (see sidebar) to determine whether changes due to advanced technologies are appearing in employment data. By exploring concentrations of these occupations in industries, job displacements in these occupations, and the characteristics of workers in these occupations, we found minor indications that advanced technologies are changing the workforce and could affect some worker populations. However, the conclusions that can be drawn from these analyses are limited by the unpredictability of when, if, or how automation materializes—e.g., whether worker positions are eliminated or shifted to other non-automated tasks.

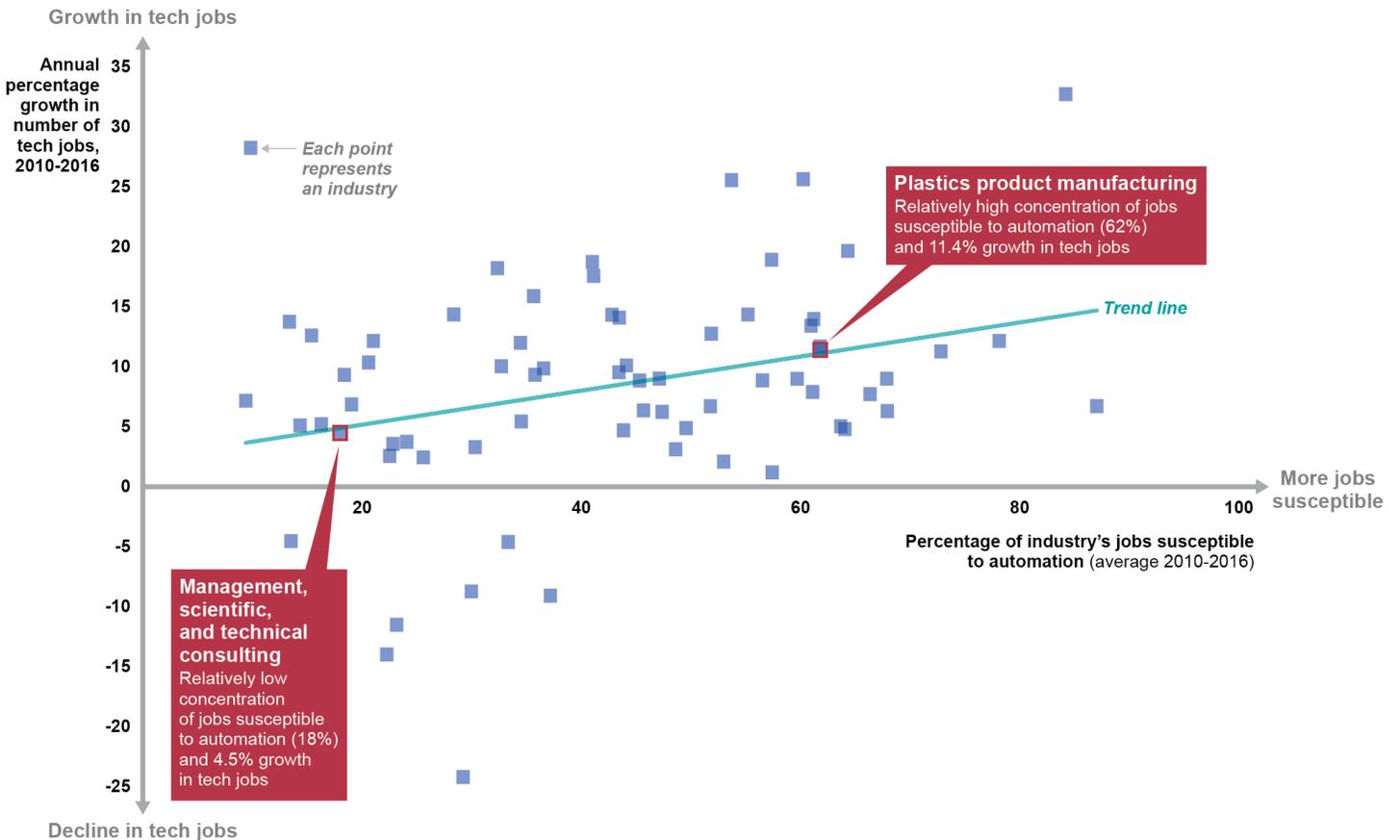
Industries with higher concentrations of jobs susceptible to automation were more likely than others to have experienced significant growth in their concentration of tech jobs from 2010 to 2016, according to our analysis of employment data from the American Community Survey. For example, as shown in figure 2, the plastics product manufacturing industry has a relatively high concentration of jobs susceptible to automation. Many of these jobs are in production occupations. From 2010 through 2016, this industry experienced about 11 percent annual growth in tech jobs (i.e., jobs in the fields of computing, engineering, and mathematics). More than half of this growth was the result of increases in industrial engineers, engineering technicians, and miscellaneous engineers.²⁸ As we observed at some firms we visited, some of these engineers may have been hired to program or maintain newly installed robots. However, the data do not provide this level of information about job tasks. Similar dynamics could also be occurring in other industries. Across all 69 industries that had statistically significant changes in the concentration of tech jobs, we found a positive, though weak, correlation

²⁸ We approximated each occupation’s contribution to the overall growth of tech jobs in the industry by multiplying their individual growth rates over the period 2010-2016 by their employment in 2010. The growth rates for the three engineering occupations we discuss were each significant at the 85 percent confidence level.

with the concentration of jobs susceptible to automation (see fig. 2).²⁹ This suggests that growth in tech jobs may be an indicator of industries' preparation for, or adoption of advanced technologies. However, given the complex causes of employment changes, there could be other reasons for tech job growth in these industries that are unrelated to firms' adoption of advanced technologies.

²⁹ We analyzed jobs in occupations that researchers Frey and Osborne identified as susceptible to automation. We examined the relationship between industries and tech employment by estimating both Pearson and Spearman correlations (correlations of numbers and ranks, respectively). We limited our analysis to the 69 industries that had statistically significant trends in the concentration of tech jobs during the period 2010-2016. The Pearson correlation number was 0.30, and the Spearman correlation number was 0.23. We define tech jobs consistent with GAO, *Diversity in the Technology Sector: Federal Agencies Could Improve Oversight of Equal Employment Opportunity Requirements*, [GAO-18-69](#) (Washington, D.C.: November 16, 2017). We also conducted sensitivity analyses using an alternative measure of tech jobs and found similar results. See appendix I for more information.

Figure 2: Correlation between an Industry's Concentration of Jobs Susceptible to Automation and That Industry's Growth in Tech Jobs, 2010-2016



Source: GAO analysis of employment data from the American Community Survey (ACS), 2010-2016. | GAO-19-257

Notes: The figure depicts the association between an industry's percentage of jobs susceptible to automation and its annual percentage growth in the number of tech jobs from 2010 through 2016. We limited our analysis to the 69 industries that had statistically significant trends in the concentration of tech jobs at the 95 percent confidence level. The trend line represents the predicted value from a linear regression, and the Pearson correlation value of the data depicted in the figure is 0.30. The percentages of jobs susceptible to automation for all industries have relative margins of error within +/- 10 percent of the estimate themselves. Tech jobs are those in occupations in the fields of computing, engineering, and mathematics. Occupations susceptible to automation are those that researchers Frey and Osborne estimated as having a probability of automation greater than 0.7—see Carl Frey and Michael Osborne, "The Future of Employment: How Susceptible Are Jobs to Computerisation?," *Technological Forecasting & Social Change* (2016).

The growth in tech jobs in certain industries suggests firms in these industries may be using more advanced technologies, which could also signal that jobs susceptible to automation are being replaced. However, our analysis of ACS data showed no correlation between an industry

having a higher concentration of jobs susceptible to automation and employment changes in that industry (i.e., total employment increases or decreases).³⁰ We also found no meaningful differences in job losses, according to our analysis of employment data from the Current Population Survey's Displaced Worker Supplement. Specifically, the relative rate at which workers in occupations susceptible to automation lost a job because their position or shift was abolished or there was insufficient work for them to do was not meaningfully different than workers in other occupations.³¹ There could be a number of reasons we did not find a relationship between susceptibility to automation and employment changes in both of these analyses, including:

- a relationship does not exist;
- such a relationship is too complex to measure in this way (e.g., automation may lead to decreases in employment in some industries, while also leading to increases in employment in other industries due to improved competitiveness, productivity, and profitability);
- it is too soon to observe the employment effects of automation (e.g., growth in tech jobs in an industry may be a leading indicator of employment disruption);³² or
- our analysis covered a period of overall economic growth, which could obscure or overwhelm other employment trends.

³⁰ We analyzed the relationship between industries and employment changes by estimating both Pearson and Spearman correlations (correlations of numbers and ranks, respectively). We limited our analysis to those 125 industries that had statistically significant trends in employment (increases or decreases) during the period 2010-2016. The Pearson correlation number was -0.01, and the Spearman correlation number was 0.03.

³¹ We analyzed jobs in occupations that researchers Frey and Osborne identified as susceptible to automation. We calculated relative job displacement rates as the number of job displacements over the period 2013-2015 for a given set of occupations, divided by total current employment in that set of occupations in January 2016. Jobs susceptible to automation had a relative displacement rate of 3.4 percent +/- 0.3, and all other jobs combined had a relative displacement rate of 2.9 percent +/- 0.2. As sensitivity tests, we also examined different groups of occupations (see app. I for more information).

³² Frey and Osborne's study projected susceptibility to automation using data on work tasks as of 2010 and our analysis examines the period 2010-2016. This relatively short period may not be long enough to observe aggregate changes in employment levels resulting from advanced technologies.

Existing data cannot predict with certainty when or if automation will materialize in the workforce, as suggested by our analyses. However, the tendency of particular worker groups to hold jobs susceptible to automation suggests that some communities may be disproportionately affected by changes if they occur. For example, according to our analysis of 2016 ACS data, workers with lower levels of education are more likely than those with higher levels to hold jobs in occupations that the Frey and Osborne study identify as susceptible to automation. Specifically, 60.7 percent of workers with a high school degree or less hold these types of jobs, as compared to 46.7 percent of workers with some college, 26.9 percent of workers with a bachelor's degree, and 11.3 percent of workers with a graduate degree. In addition, 54.1 percent of Hispanic workers hold jobs in occupations susceptible to automation, as compared to 46.4 percent of Black workers, 40.0 percent of White workers, and 35.9 percent of Asian workers.³³

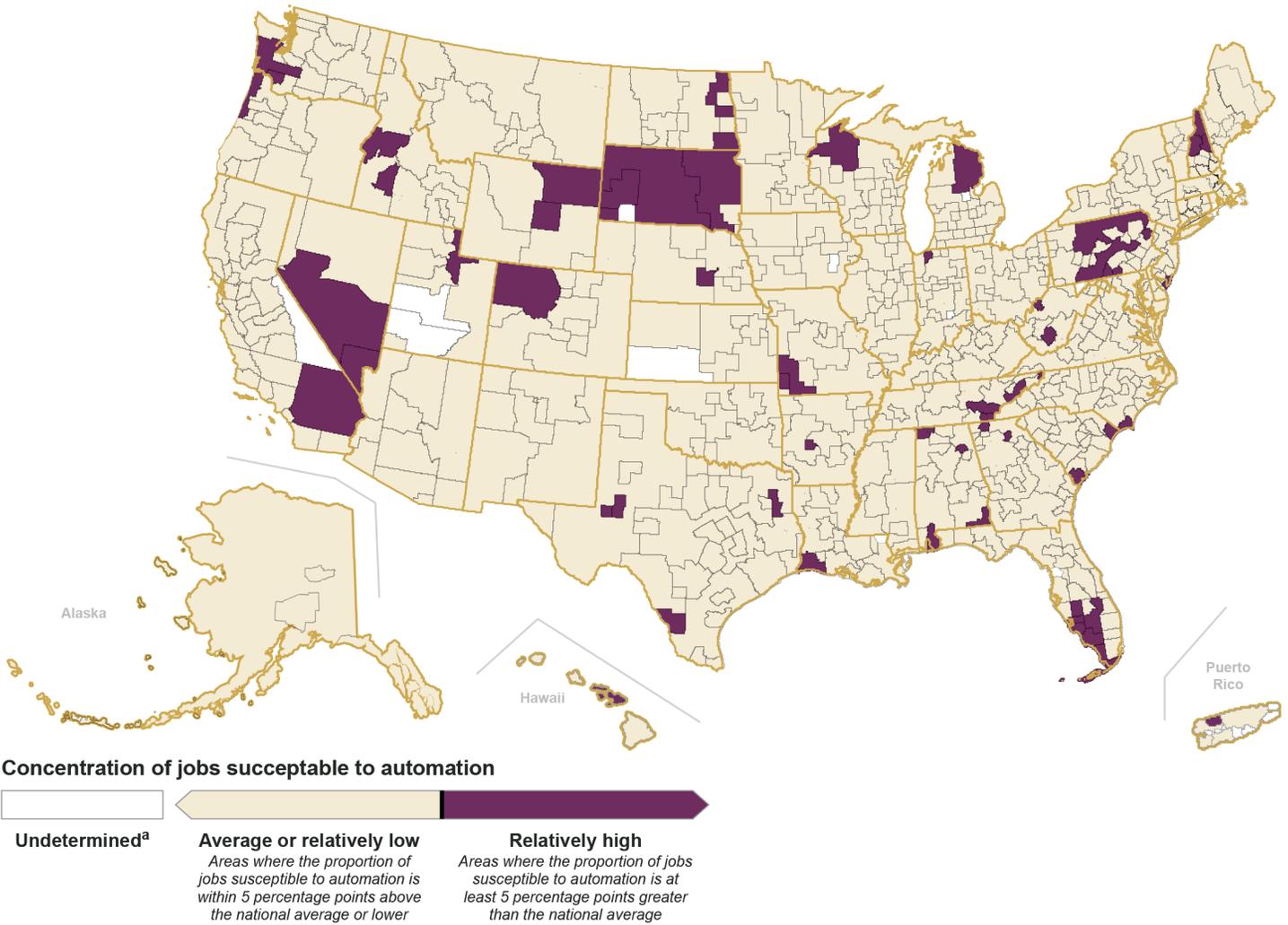
Certain geographic areas also rely more heavily than others on occupations identified as susceptible to automation, according to OES data. We identified areas where the proportion of jobs susceptible to automation is at least 5 percentage points greater than the national average (see fig. 3).³⁴ These occupations are comprised of a diverse set of jobs that may experience automation in different ways and at different times, if at all. However, if employment disruptions are regionally concentrated, groups of workers with similar skills in the same labor market may need to adapt to changes simultaneously, which could strain the availability of local job opportunities and support resources.³⁵

³³ Comparison race groups include only non-Hispanic workers. All percentages shown have relative margins of error within +/- 0.65 percentage points or less of the estimates themselves, at the 95 percent confidence level. For comparisons of age and gender, as well as information about the characteristics of workers with tech jobs, see appendix I.

³⁴ We measure an area's reliance on jobs susceptible to automation (as identified by Frey and Osborne) by comparing the proportion of those jobs in each local geographic area to the proportion of those jobs nationwide. We then identified areas where the proportion of jobs susceptible to automation is at least 5 percentage points greater than the national average, significant at the 95 percent confidence level. Local geographic areas include both metropolitan statistical areas and nonmetropolitan areas. For more information about our methods for mapping the OES data, including considerations for analyzing multiple occupations in combined groups (some of which have data suppressed in certain areas), see appendix I.

³⁵ For additional discussion of the implications of regional concentrations of employment disruptions, see Erica Groshen, et. al., *Securing America's Future Energy (SAFE)*, "Preparing U.S. Workers and Employers for an Autonomous Vehicle Future" (June 2018).

Figure 3: Geographic Concentration of Jobs Susceptible to Automation



Source: GAO analysis of data from the May 2017 Occupational Employment Statistics (OES). | GAO-19-257

Notes: The map depicts the proportion of each local geographic area’s jobs in occupations susceptible to automation compared to the national proportion of employment in these occupations—in other words, how great an extent to which a local geographic area relies on certain jobs for the employment of its population, relative to other areas. The differences between areas with relatively high concentrations and the national average are statistically significant at the 95 percent confidence level. Local geographic areas include both metropolitan statistical areas and nonmetropolitan areas. The 2017 OES data estimates are based on surveys conducted over the period November 2014 through May 2017. Occupations susceptible to automation are those that researchers Frey and Osborne estimated as having a probability of automation greater than 0.7—see Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016).

^aWe classify an area’s proportion as “undetermined” if the estimated margin of error at the 95 percent confidence level is larger than 5 percentage points.

Workers in occupations that the Frey and Osborne study identify as susceptible to automation earn less on average than other workers. For example, the median hourly wage for workers in occupations susceptible to automation is \$14.26, compared to \$22.06 for other workers, according to our analysis of 2016 ACS data. After controlling for factors that may affect wages, such as age, education, and industry, we found that workers in jobs susceptible to automation earn about 17.2 percent less, on average, than similar workers in other occupations.³⁶ These results show that, on average, workers in jobs susceptible to automation are already in more vulnerable economic circumstances than other workers. When or if changes brought on by automation materialize, these workers may face additional hardships in adapting to changing workforce demands.

Examples of Other Researchers' Analyses that Attempt to Measure Workforce Effects Due to Advanced Technology Adoption

In the absence of comprehensive data, researchers have taken differing approaches to exploring the relationships between technology adoption and workforce trends. We identified some examples of recent and ongoing work that attempt to measure workforce effects directly attributable to technology adoption. These examples illustrate types of data that may be useful for better understanding and measuring the use of specific technologies (e.g., robot sales), the spread of technologies generally (e.g., automation patents), and how specific work tasks are changed by technology use (e.g., firm-level operations data).

Some researchers have used data on industrial robot sales collected by the International Federation of Robotics (IFR) to approximate robotics adoption worldwide and in the United States and to model its direct effects on employment.³⁷ Analysis by Furman and Seamans (2018) shows that annual sales of industrial robots in the United States

³⁶ Our regression analysis controlled for age, race and ethnicity, gender, marital status, state of residence, education level, and industry. The regression results are statistically significant at least at the level of p-value < 0.05. Various independent variables capture and control for different characteristics across workers, yet unobservable factors that may cause earnings differences may exist; thus, regression results do not prove causality. Occupations susceptible to automation are those identified by researchers Frey and Osborne. For more information, see appendix I.

³⁷ IFR data include counts of robot sales by destination country and industry, among other things. The IFR data on robot sales have some key limitations, including their aggregate nature obscuring differences within industries and differences in complexity (e.g., complex robots are counted the same as simpler robots).

increased substantially between 2010 and 2016.³⁸ The analysis attributes this growth to a combination of factors, including lower robot prices, improved robot functionality, and greater awareness of the benefits of robots. They also observe that the automotive sector was the largest customer for industrial robot sales in the United States from 2004 through 2016, though robot sales to the consumer electronics sector grew the most over that period.

Studies by Acemoglu and Restrepo (2017) and by Graetz and Michaels (2017) both use IFR data through 2007 to model the workforce effects of robot adoption in the United States, though their methods, results, and conclusions differ.

- Acemoglu and Restrepo estimate that each additional robot used in a geographic area reduces employment by about six workers in that area. They observe that their estimated employment effects are greatest in manufacturing and other industries most exposed to robots, in routine manual work-related occupations, and for workers with less than a college education. They do not find corresponding employment gains in any other occupation or education groups. They also estimate that one more robot used per thousand workers reduces wages by about 0.5 percent. They conclude by noting that, so far, relatively few robots have been used in the U.S. economy and thus the effect on jobs has been limited; however, they state that if robot usage continues to grow as researchers expect, these effects could be more substantial.³⁹
- Graetz and Michaels estimate that increased robot use did not significantly affect total hours worked across the 17 developed countries in their analysis, but that work shifted from low-skilled workers to middle-skilled and high-skilled workers. They also estimate that increased robot use increases productivity and average wages. While their analysis covers 17 developed countries, they note that

³⁸ Jason Furman and Robert Seamans, "AI and the Economy," *NBER Working Paper Series*, Working Paper 24689 (Cambridge, MA: National Bureau of Economic Research, June 2018).

³⁹ Acemoglu and Restrepo estimate the impact of industrial robots on employment and wages in the United States between 1990 and 2007. The study uses IFR data and U.S. employment data from decennial censuses and the American Community Survey. Daron Acemoglu and Pascual Restrepo, "Robots and Jobs: Evidence from US Labor Markets," *NBER Working Paper Series*, Working Paper 23285 (Cambridge, MA: National Bureau of Economic Research, March 2017).

robot use in the United States was marginally lower than the average across all countries. They also observe that while their results differ from Acemoglu and Restrepo, it is possible that the effects of robot usage are different in the United States than across the 17 countries they analyze.⁴⁰

Other researchers have used U.S. patent data as an alternative way to approximate the spread of advanced technologies and to examine the resulting workforce effects. Mann and Püttman (2017) use machine learning algorithms to identify patents related to automation technology. They find that automation patents grew substantially from 1976 through 2014.⁴¹ After linking the patents to industries where they may be used, they estimate that automation causes manufacturing employment to fall, though it increases employment in the service sector, as well as overall employment. They observe that their results depict a more positive picture of the employment effects of new technology use than the studies that used industrial robot sales data (discussed above).⁴² Lee Branstetter, a researcher at Carnegie Mellon University, and his colleagues have a similar ongoing project that uses a machine learning algorithm to identify patents related to AI technologies. According to these researchers, their initial results suggest a rapid rise in AI patents over the past decade and also that AI patents are emerging in a variety of application areas. They are also in the early stages of work linking AI patents to industries to explore how new technology use affects the workforce.

Researchers have also identified how important micro-level data could be for understanding the workforce effects of advanced technology adoption.

⁴⁰ Graetz and Michaels estimate the impact of industrial robots on employment across 17 developed countries—including the United States—between 1993 and 2007. The study uses IFR data and employment data from EUKLEMS, which includes U.S. data compiled from Bureau of Economic Analysis and Bureau of Labor Statistics sources. Georg Graetz and Guy Michaels, “Robots at Work,” *Centre for Economic Performance Discussion Paper No. 1335* (London: Centre for Economic Performance, March 2015; updated version of paper from June 2017).

⁴¹ Officials from the U.S. Patent and Trademark Office told us that there has been small but steady growth in patents in recent years, but that patents related to automation and artificial intelligence have been growing steeply and have far outpaced overall growth.

⁴² Mann and Püttman estimate the impact of new technology use on employment in the United States between 1976 and 2014. The study uses U.S. patent data, as well as U.S. employment data from the County Business Patterns dataset. Katja Mann and Lukas Püttmann, “Benign Effects of Automation: New Evidence from Patent Texts” (paper presented at the annual meeting of the Allied Social Science Associations, Philadelphia, PA: January 2018—paper dated December 2017).

For example, reports by the National Academies and others highlight the potential for firm-level information to augment traditional survey data to enable analyses of the conditions under which advanced technologies complement or substitute for workers, and what types of firms invest in advanced technologies.⁴³ Other researchers have emphasized the importance of focusing on work tasks to analyze the effects of technological change at workplaces.⁴⁴ Erica Fuchs, a researcher at Carnegie Mellon University, and her colleagues Christophe Combemale, Katie Whitefoot, and Laurence Ales use a combined firm-level, task-based approach by collecting and analyzing production floor data from four semiconductor firms with different levels of process automation and parts consolidation. They map out detailed versions of firms' production processes and then use existing data and technical knowledge to simulate each step to analyze the effects of technology changes. Their preliminary results estimate that automation replaces some routine tasks, leading to estimated declines in the number of production floor jobs requiring medium skill levels. According to the authors, this firm-level, task-based approach may be applicable to other manufacturing industries and could provide insight on how the adoption of different technologies may produce different labor outcomes. However, they note that the approach requires detailed production process data, which may be difficult to collect for many firms or industries.⁴⁵

⁴³ See National Academies, *Information Technology and the U.S. Workforce*, and Robert Seamans and Manav Raj, "AI, Labor, Productivity and the Need for Firm-Level Data," *NBER Working Paper Series*, Working Paper 24239 (Cambridge, MA: National Bureau of Economic Research, January 2018; updated version of paper from April 2018).

⁴⁴ For example, the co-chairs of the National Academies report, as part of a different project, developed a rubric to determine the suitability of various tasks to be automated by machine learning and used this data to analyze workforce effects; see Erik Brynjolfsson and Tom Mitchell, "What Can Machine Learning Do?: Workforce Implications," *Science*, vol. 358, no. 6370 (December 2017), with supplementary materials referred to in article, and also Erik Brynjolfsson, Tom Mitchell, and Daniel Rock, "What Can Machines Learn and What Does It Mean for Occupations and the Economy?" *AEA Papers and Proceedings*, vol. 108 (May 2018). See also Daron Acemoglu and David Autor, "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, vol. 4b (2011).

⁴⁵ Christophe Combemale, Kate Whitefoot, Laurence Ales, and Erica Fuchs, "Not All Technological Change is Equal: Disentangling Labor Demand Effects of Automation and Parts Consolidation," Carnegie Mellon University Working Paper (November 2018; available at SSRN). The study also observes that tasks created by automation tend to require low and high skills (e.g., pressing a button or calibrating a machine).

Commerce and DOL Have Some Efforts to Track Adoption and Workforce Effects of Advanced Technologies

Commerce Has Started Tracking Technology Adoption and Resulting Workforce Effects, but Data Will Not Be Available until Late 2019

Survey Questions on Automation

The Annual Business Survey also collects information about firms' process innovations and machinery investments, both of which can represent forms of automation or advanced technology adoption. However, officials at the Census Bureau and National Science Foundation cautioned that it is unknown how closely responses to these questions will approximate actual technology adoption. Officials stated that advanced technology is only one driver of process innovation, and there are likely other drivers that will be captured under these questions.

Source: GAO analysis of 2017 Annual Business Survey questionnaire and interviews with officials at the Census Bureau and National Science Foundation. | GAO-19-257

Commerce's Census Bureau has begun administering surveys with questions that focus specifically on firms' adoption of advanced technologies and resulting workforce changes. According to Census, this data collection is part of a long-standing, coordinated effort to measure the impact of technology. In addition, consistent with Commerce's strategic plan, these represent new efforts to provide a timely, in-depth, and accurate picture of the economy amidst the economic shifts and technological advances of the 21st century.⁴⁶ However, none of the survey results will be available until late 2019 and later.⁴⁷

The new Annual Business Survey (ABS) is a joint effort by Commerce and the National Science Foundation that has the potential to provide insight on the spread of advanced technologies in the economy and could be used to examine the workforce effects of technology adoption, but the first ABS results are not expected until late 2019.⁴⁸ Census administered the 2017 ABS in June 2018 to collect information on firms' use of advanced technologies, such as automated guided vehicles, machine learning, machine vision, and robotics, among other things (see example in sidebar). The survey asks whether firms are testing a given technology or using it for either less than 5 percent, 5 to 25 percent, or more than 25

⁴⁶ Department of Commerce, *Strategic Plan, 2018 – 2022, Helping the American Economy to Grow* (Washington, D.C., February 13, 2018).

⁴⁷ According to Census, the planned dates discussed in this report for survey data collection and publication may be affected by the agency's lapse in appropriations during fiscal year 2019.

⁴⁸ The Annual Business Survey is a joint effort by the Census Bureau and the National Center for Science and Engineering Statistics within the National Science Foundation. Census plans to administer the survey annually for 5 years. According to officials, NSF is covering about 80 percent of the 5-year cost of the ABS and has been heavily involved in developing the questions.

percent of their production or service.⁴⁹ Census officials said this question should provide information about the extent of technology adoption nationwide, including whether there are any industry concentrations of advanced technologies.⁵⁰

Census plans to add questions on the workforce effects of advanced technologies when it administers the 2018 ABS during July through December 2019, pending final approval by the Office of Management and Budget.⁵¹ Census plans to release these survey results in December 2020. Specifically, Census plans to include new questions that ask firms about: (1) their use of advanced technologies such as AI, cloud computing, robotics, and specialized software and equipment; (2) their motivation for adopting and using artificial intelligence and advanced technologies; (3) the impact these technologies might have on the number and skill level of workers; and (4) the factors that could adversely affect the adoption or production of these technologies. The new questions also ask about changes in the number of production workers, non-production workers, supervisors, and non-supervisors. These new questions could be used to characterize the prevalence of workforce changes in the economy caused by advanced technology adoption (e.g., declines in production workers, or increases in supervisory workers) and whether this differs by industry sector. However, these planned questions are not intended to provide information to quantify the magnitude of workforce changes, in part to minimize respondent burden and potential

⁴⁹ The full list of technologies in the survey consists of augmented reality; automated guided vehicles systems; automated storage and retrieval systems; machine learning; machine vision software; natural language processing; radio-frequency identification inventory system; robotics; touchscreens/kiosks for customer interface (e.g., self-checkout, self-check-in, touchscreen ordering); and voice recognition software. According to NSF officials, the list of technologies was developed in consultation with an expert in the field.

⁵⁰ A prior Census survey, the Survey of Manufacturing Technology, which was administered in 1988, 1991, and 1993, similarly measured the use of advanced technologies in the manufacturing sector. The Department of Defense, for example, used the survey data to assess the diffusion of technology.

⁵¹ The Paperwork Reduction Act requires Census and other agencies to obtain approval for their information collection instruments from the Office of Management and Budget. 44 U.S.C. § 3507. Census plans for the 2018 ABS to survey approximately 300,000 companies across all non-farm sectors of the economy. Census plans to publish survey results at the sector level for national, state and select Metropolitan Statistical Area geographies.

survey error, according to Census.⁵² In addition, until the ABS data are available and evaluated, it remains unclear what limitations, if any, the data may have.

Census also plans to expand other surveys to track the spread of advanced technologies in the economy, including its Annual Survey of Manufactures (ASM) and Annual Capital Expenditures Survey (ACES).⁵³

- Census plans to administer the 2018 ASM in May 2019, pending final approval by the Office of Management and Budget. The survey will collect capital expenditures data for industrial robotics at approximately 50,000 manufacturing plants, as well as the number of industrial robots purchased by and in use at these plants.⁵⁴ Census officials stated these two measures might be useful in understanding the impact that industrial robots could have on productivity as well as the impact robots could have on the manufacturing labor force once the survey results are available in the spring of 2020.
- Census plans to administer the 2018 ACES during March through May 2019 and to have the survey results available in February 2020. The survey will include questions on robotics expenditures, similar to those in the 2018 ASM.⁵⁵ However, the ACES collects expenditure data from 50,000 employer firms across all non-farm

⁵² The planned questions ask whether employment increased, decreased, or did not change at a firm, rather than how many jobs were lost or gained. According to Census, the agency will be able to use administrative data to calculate changes in overall employment, rather than relying on respondents' memories or requiring additional data searches and calculations by respondents. In addition, Census will be able to use its survey collections and other data to characterize workers at firms that adopt or do not adopt advanced technologies.

⁵³ The 2018 Business R&D and Innovation Survey will be administered from February through December 2019, pending final approval by the Office of Management and Budget, and it will ask firms the amount of research and development spending they are directing towards artificial intelligence.

⁵⁴ The Annual Survey of Manufactures collects information from manufacturing establishments with one or more paid employee on employment, payroll, operating expenses, value of shipments, value added by manufacturing, and detailed capital expenditures, among other things. The survey is conducted annually, except for years ending in 2 and 7, at which time ASM statistics are included in the manufacturing sector of the Economic Census.

⁵⁵ The Annual Capital Expenditures Survey collects detailed information on capital investment in structures and equipment, among other things, by nonfarm enterprises.

sectors of the economy—instead of just manufacturers—and will also ask about firms’ use of both industrial and service robots.

Some Commerce offices also track issues related to the adoption and workforce effects of advanced technologies on a limited or intermittent basis. For example, National Institute of Standards and Technology officials stated that the Hollings Manufacturing Extension Partnership collects limited information about the number of jobs gained and retained by small and medium businesses adopting new technologies. National Telecommunications and Information Administration officials said they monitor developments in AI on an intermittent basis and also direct a project that examines new applications of small and large internet devices.

DOL’s Current Efforts Provide Limited Information for Tracking the Workforce Effects of Advanced Technologies

DOL has a role in collecting data that track changes occurring in the U.S. economy and workforce, including developing new ways to track emerging economic trends, though as we previously discussed, currently available federal data do not link shifts in the workforce to technological changes. BLS is the principal federal statistical agency responsible for measuring labor market activity. According to DOL’s strategic plan, BLS is to support public and private decision-making and meet the needs of its many stakeholders, including the general public, educational institutions, and the public workforce system. This includes regularly identifying structural shifts in the economy and developing new data products that reflect economic changes.⁵⁶ In addition, DOL’s Employment and Training Administration (ETA) is to assist workers’ entry and reentry into in-demand industries and occupations. This assistance includes providing job seekers with accurate labor market data and guidance about opportunities, aligning training services to industry needs, and helping connect businesses with properly skilled workers. Internal control standards state that agencies should use quality information to identify, analyze, and respond to significant changes, including external conditions such as economic and technological changes that may affect an agency’s ability to achieve its objectives.⁵⁷ DOL collects workforce data through various surveys, including the Current Population Survey’s Displaced Worker Supplement, and produces other data products such as the

⁵⁶ Department of Labor, *FY 2018-2022 Strategic Plan* (Washington, D.C., 2018).

⁵⁷ GAO, *Standards for Internal Control in the Federal Government*, [GAO-14-704G](#) (Washington, D.C.: September 2014).

Employment Projections

occupational employment projections and Occupational Information Network database that include information related to advanced technologies. However, these data are limited, and according to BLS, provide some, but not all, of the information required to assess the impact of automation on the workforce.

BLS's Employment Projections program identifies and provides limited information about occupations expected to experience declines in their share of employment in an industry or group of industries as a result of the adoption of advanced technologies. On a biennial basis, this program analyzes changes in the economy to project how employment by occupation may change over 10 years, including which occupations may be affected by advanced technologies.⁵⁸ Factors that can affect occupational employment include but are not limited to technological innovation; changes in business practices or production methods; organizational restructuring of work; changes to the size of business establishments; and offshore and domestic outsourcing, according to BLS. As part of this program, BLS develops a table of occupations that are projected to have direct employment changes due to some identified reason.⁵⁹ This table identifies projected staffing pattern changes and BLS's qualitative judgment of the most significant factor or factors projected to affect the occupation. The table also indicates whether an occupation's share of employment is expected to change within a single industry or within multiple or all industries. For example, the table includes the following selected entries:

- **Librarians:** Employment share is projected to decline in the information services industry as internet-based research continues to displace library-based research.
- **Stock clerks and order fillers:** Employment share is projected to decline in two industries (the warehousing and storage industry and

⁵⁸ According to BLS officials, research to develop occupational projections includes reviews of literature and economic studies, outreach to experts, industry contacts, and trade associations, and also quantitative analysis of historical OES employment data.

⁵⁹ Bureau of Labor Statistics, *Table 5.1: Factors Affecting Occupational Utilization, Projected 2016–26*, Employment Projections program, accessed November 5, 2018, <https://www.bls.gov/emp/tables/factors-affecting-occupational-utilization.htm>. *Table 5.1* only captures active staffing pattern changes, as opposed to downstream effects (i.e., automation in one occupation affecting employment in a different occupation), according to BLS officials. In addition, some staffing pattern changes are not reflected in this table because the information for a certain occupation is not publicly releasable.

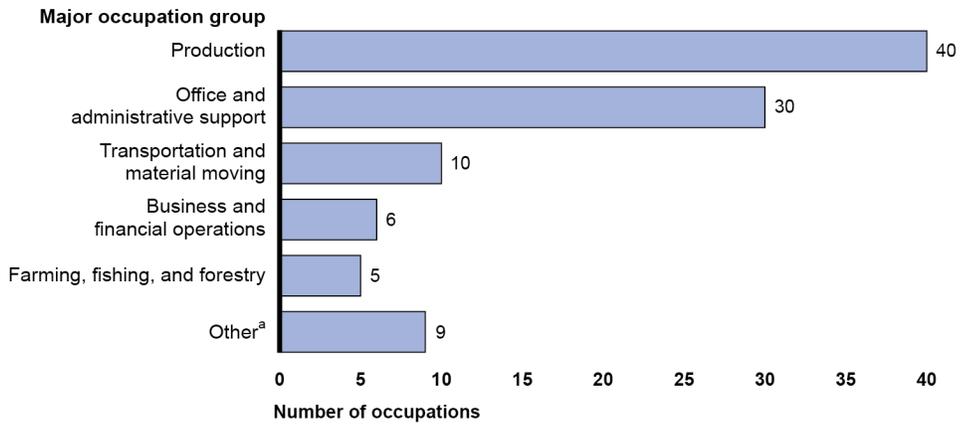
the grocery and merchant wholesalers industry) as firms increasingly adopt automated storage-and-retrieval systems.

- **Aircraft structure and systems assemblers:** Employment share is projected to decline in all industries as collaborative robotics increase efficiency, producing more output with the same amount of labor.

We identified 100 occupations in BLS's table that are projected to experience declines in their shares of employment in an industry or group of industries as a result of the adoption of advanced technologies.⁶⁰ Similar to the examples above, reasons could be related to automation, the increased use of robots or artificial intelligence, advances in machine or software technologies, or other changes resulting from the adoption of advanced technologies. As shown in figure 4, most of these occupations are production occupations (40 of 100) or office and administrative support occupations (30 of 100). BLS officials told us they do not currently track groups of occupations projected to experience employment share declines due to specific reasons, such as advanced technology adoption. Officials also said they do not aggregate total projected employment effects stemming from similar causes because they are unable to identify ripple effects in all occupations—e.g., automation in one occupation affecting employment in a different occupation.

⁶⁰ BLS's projections are for the most part structured around the Occupational Employment Statistics, which produces employment and wage estimates for over 800 occupations. Overall projections are based on a combination of industry changes and staffing pattern changes. Not all occupations are included in *Table 5.1* because only staffing pattern changes are identified and discussed in this table and for many occupations, these are projected to remain unchanged, according to BLS. BLS includes 247 unique occupations in its table, some of which are projected to experience employment share increases and some decreases. The employment share declines identified by BLS do not imply that occupations will be eliminated and may not necessarily mean employment in a given occupation will decrease in absolute terms. Rather, an employment share decline indicates that employment in an occupation will decline relative to others in a given industry or group of industries. See appendix I for more information.

Figure 4: Occupations BLS Projects Will Experience Declines in Their Shares of Employment in an Industry or Group of Industries Due to the Adoption of Advanced Technologies, Projected 2016–26



Source: GAO analysis of Bureau of Labor Statistics (BLS) Employment Projections data. | GAO-19-257

Notes: As part of its Employment Projections program, BLS develops a table of occupations that it projects will experience direct staffing pattern changes due to some identified reason, based on BLS's qualitative judgment of the most significant factor or factors projected to affect the occupation. We identified the 100 occupations shown in the figure as those projected to experience declines in their shares of employment in an industry or group of industries broadly as a result of the adoption of advanced technologies—e.g., due to automation, the increased use of robots or artificial intelligence, advances in machine or software technologies, or other changes. The employment share declines identified by BLS do not imply that the number of jobs in an occupation will necessarily decrease in absolute terms. Rather, an employment share decline indicates that employment in an occupation will decline relative to others in a given industry or group of industries. BLS includes 247 unique occupations in its table, some of which are projected to experience employment share increases and some decreases. We categorize the 100 occupations according to their major occupation group, defined by the Standard Occupational Classification (SOC) system.

^aOther major occupation groups include: educational instruction and library; protective service; installation, maintenance, and repair; life, physical, and social science; arts, design, entertainment, sports, and media; and sales and related.

Occupational Information Network

Information contained in ETA's Occupational Information Network (O*NET) database includes, among other things, information about work activities, tools and technologies used, and required skills associated with

over 1,000 occupations.⁶¹ According to ETA officials, the primary purpose of O*NET is to assist job seekers in making employment decisions. However, the O*NET database can be used to identify occupations that use certain types of advanced technologies. For example, we identified 15 occupations in which workers monitor, install, develop, troubleshoot, debug, or perform other tasks with robots as part of their daily work activities and 63 occupations in which workers use robots as a tool or technology in their daily work activities (see table 1).⁶² In addition, states, federal officials including at BLS, and academic researchers use these data to inform, among other things, worker support programs. DOL officials told us they do not use O*NET data to analyze changes in occupations over time, such as robots being used in additional occupations, because the methodology is not currently structured to capture these kinds of changes systematically. For example, data are collected from a selection of occupations at varying frequencies, rather than at the same time, which could make it challenging to track changes in certain occupations over time.

Table 1: Examples of Occupations Using Robotics as a Tool or Technology in Daily Work Activities

Occupation Title	Tool Example
Environmental Engineering Technicians	Robotic or automated liquid handling systems
Broadcast Technicians	Robotic studio cameras
Municipal Firefighters	Explosive detection robots
Electrical Power-Line Installers and Repairers	Robotic arms
Painters, Transportation Equipment	Robotic paint equipment

Source: GAO analysis of information contained in the Occupational Information Network (O*NET) database. | GAO-19-257

⁶¹ O*NET is sponsored by DOL's ETA through a grant to the North Carolina Department of Commerce, according to DOL. The U.S. Department of Commerce used O*NET data in conjunction with other data sources for its study on *The Employment Impact of Autonomous Vehicles*. Commerce officials stated that they used O*NET data to examine the occupational characteristics of drivers—such as their work activities and the tools and technology they use. See David Beede, Regina Powers, and Cassandra Ingram. *The Employment Impact of Autonomous Vehicles*, Office of the Chief Economist, Economics and Statistics Administration, U.S. Department of Commerce. ESA Issue Brief # 05-17 (August 11, 2017). Researchers have also used O*NET data to develop projections of the future workforce effects of advanced technologies and automation.

⁶² See appendix I for more information about our analysis of O*NET data.

Lack of Comprehensive Data

Without comprehensive data linking employment shifts and technological changes, policymakers and DOL may not be prepared to design and implement programs that both encourage economic growth and provide support for workers affected by changes. DOL-funded programs rely on accurate information to guide job seekers to employment opportunities and to help align training services with local industry needs. For example, the O*NET database identifies high-growth, high-demand occupations for job seekers based largely on BLS employment projections data. While these employment projections provide valuable information, they are not designed to identify the full extent of occupational shifts due to advanced technology adoption. Similarly, other workforce surveys, such as the Current Population Survey's Displaced Worker Supplement and the Job Openings and Labor Turnover Survey, do not collect information about the causes of job losses and gains. This information could be a valuable tool for designing programmatic or policy supports for workers. For example, data on whether advanced technologies have resulted in worker displacements, work hour reductions, or substantial adjustments to work tasks could better position BLS to meet stakeholder needs.

Congress has expressed concern that there continues to be insufficient data on the effects advanced technologies are having on the U.S. workforce.⁶³ On January 2, 2019, BLS reported to Congress that it plans to work with a contractor during fiscal year 2019 to study the interaction between labor and capital in the workplace and how it is affected by new technologies; identify ways to supplement BLS data with additional information on automation; and produce a report that recommends data collection options to fill those gaps. In fiscal year 2020, BLS also plans to identify pilot projects to test the feasibility of new data collection based on the recommendations in its final report, resources permitting.⁶⁴ However, these plans are still in their early stages, according to BLS officials.

⁶³ The Conference Report accompanying the Department of Defense and Labor, Health and Human Services, and Education Appropriations Act, 2019 and Continuing Appropriations Act, 2019 directs BLS to submit a report to the Committees on Appropriations of the House of Representatives and the Senate no later than 90 days after enactment of the act detailing the steps taken to develop the data strategy. See H.R. Rep. No. 115-952, Div. B, at 516 (2018) (direction to BLS incorporated by reference from S. Rep. No. 115-289, at 38).

⁶⁴ Bureau of Labor Statistics, "Report to the Committees on Appropriations of the House of Representatives and the Senate on Measuring the Effects of New Technologies on the American Workforce" (January 2019).

Commerce and DOL Face Challenges Tracking the Workforce Effects of Advanced Technologies

Officials at Commerce and DOL stated that collecting data on the adoption and workforce effects of advanced technologies is challenging because it is difficult to identify which new and emerging technologies to track; employment trends generally occur at the occupation and industry levels but the effects of advanced technologies typically occur at the task or job level; and employment trends have a complex and diverse set of causes. Specifically:

- **Identifying which new and emerging technologies to track.** Census officials said there is uncertainty about how an emerging technology might affect the economy and thus whether it should be tracked systematically. For example, self-service technology appeared at grocery stores in 1916, other self-service technology appeared at gas stations later, and more recently self-service technologies are being adopted by some restaurants, according to researchers. Periodically, Census has included questions in its firm surveys about the use of these technologies.⁶⁵ Past surveys asked questions about the use of self-service at gas stations until the technology became ubiquitous and was dropped from the survey. As self-service technologies have expanded to other areas of the economy such as restaurants, Census has again added questions about self-service to recent surveys because information is lacking on the growth of this phenomenon.
- **Trends and effects appear at different levels.** BLS officials said employment changes due to technology typically occur at the individual task or job level and employment trend data are at the industry and occupation levels. Officials also said that identifying technology-related effects in occupations, such as changes related to uses of machine learning algorithms, is difficult because some workers within an occupation might be affected by the technology while others might not. For example, some computer scientists and engineers might be involved in the development or application of machine learning algorithms while others are not.

⁶⁵ For more information, see Emek Basker, Lucia Foster, and Shawn Klimek, "Customer-Employee Substitution: Evidence from Gasoline Stations," *Journal of Economics and Management Strategy*, vol. 26 (2017); and Emek Basker, Randy Becker, Lucia Foster, T. Kirk White, and Alice Zawacki, "Chapter 3. Four Enhancements to the Economic Census: How Research Led to New Content," *Center for Economic Studies and Research Data Centers Research Report: 2017* (Washington, D.C.: U.S. Census Bureau, May 2018).

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- **Causes of trends are complex and diverse.** BLS officials said that employment trends' complex and diverse causes make it difficult to identify occupations that are changing because of advanced technologies. Changes in one occupation may have ripple effects in other occupations. Partly as a result of this complexity, BLS's Employment Projections program identifies examples of technology-impacted occupations, but it does not attempt to identify all instances where technology impacts occupations nor does it attempt to quantify an overall projected employment effect of advanced technologies.

White House Office of Science and Technology Policy Coordinates Policy and Research Activities Related to Advanced Technologies

The White House Office of Science and Technology Policy (OSTP) is responsible for coordinating AI related policy across government agencies and for overseeing the National Science and Technology Council's subcommittees and their ongoing activities.⁶⁶ For example, the Subcommittee on Machine Learning and Artificial Intelligence was originally chartered in 2016 to monitor machine learning and artificial intelligence and to watch for the arrival of important technology milestones in the development of AI, among other things. OSTP officials told us that the Subcommittee has been re-chartered, now receives direction from OSTP's Select Committee on Artificial Intelligence, and is presently focused on federal resources related to AI research and development.⁶⁷

⁶⁶ In 2016, OSTP issued two reports that examined the expected impact of AI-driven automation on the economy. See Office of Science and Technology Policy: *Artificial Intelligence, Automation, and the Economy* (Washington D.C.: 2016) and Office of Science and Technology Policy: *Preparing for the Future of Artificial Intelligence* (Washington D.C.: 2016). The National Science and Technology Council's activities include providing oversight to the Subcommittee on Advanced Manufacturing (SAM) and the Intelligent Robotics and Autonomous Systems Interagency Working Group (IRAS IWG) of the Subcommittee on Networking and Information Technology R&D. The SAM coordinates programs and activities in advanced manufacturing research and development, broadly, including intelligent manufacturing systems that may be enabled by industrial robotics. The IRAS IWG coordinates research and development related to the advancement of intelligent robotics and autonomous systems that complement, augment, enhance, or emulate human physical capabilities or embodied human intelligence across all applications and industrial sectors.

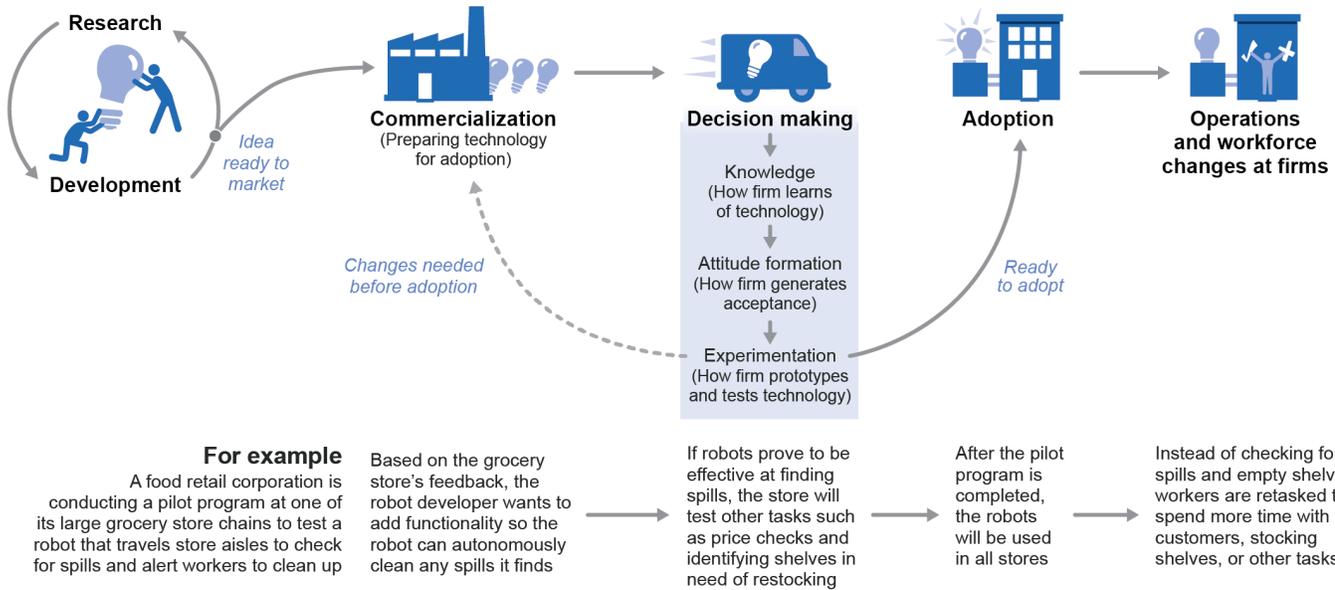
⁶⁷ In May 2018, the Select Committee on Artificial Intelligence was established by action of the National Science and Technology Council to, among other things, provide a mechanism for interagency policy coordination related to AI activities, such as autonomous systems, machine learning, and robotics.

Cost Savings and Other Considerations Motivated Selected Firms to Adopt Advanced Technologies, Despite Facing Risks Such As the Reliability of Technologies

Selected firms generally adopted advanced technologies through a phased process of innovation and technology adoption (see fig. 5). We met with officials representing 16 firms that are using advanced technologies and a systems integrator who spoke for a number of his customer firms.⁶⁸ Many firm officials described the path to integrating technology into operations as lengthy, complex, and iterative. For example, some firms we visited have had to build and test different mechanical “grippers” attached to robot arms to pick up and handle particular objects; one firm had high school participants at a local training center develop a gripper solution for one of the firm’s robots. Some of the large firms we visited had their own internal teams that identified, tested, and integrated advanced technologies. Other firms we visited used third-party integrator companies to help with incorporating technologies into their operations. We spoke with firm officials about their motivations for adopting advanced technologies, as well as challenges they faced throughout the process, and they identified a number of similar issues.

⁶⁸ The firms we met with vary by type (e.g., small manufacturer versus municipal township), size, industry sector, and types of advanced technologies used. In addition, our discussions with officials were driven by their firm’s context and thus not all firms were asked questions in exactly the same way. As a result, we report on the major themes of these discussions and use broad terms ranging from some to many to provide a general indication of how often we heard a theme.

Figure 5: A Model of the Process of Innovation and Technology Adoption by Firms



Source: GAO analysis of E.M. Rogers, *Diffusion of Innovations*, 5th ed. (New York: Free Press, 2003) and other relevant literature. | GAO-19-257

Notes: This figure depicts one of several models of the process of innovation and technology adoption by firms. Different entities may be involved in the various steps (e.g., tech developers, firm or worksite managers, and others). The overall process of innovation and technology adoption is not linear. At any point in the process, involved entities may loop back to a previous stage or jump to another stage. Similarly, an idea can be abandoned, or the decision to not adopt a technology can be made at any stage in this process.

Selected Firms Identified Cost Savings and Job Quality Among Key Motivations for Adopting Advanced Technologies

Cost Savings

Most selected firms cited cost savings as a primary consideration for adopting advanced technologies. Firm officials discussed cost-related motivations in various forms, such as remaining competitive in a global economy, increasing productivity (i.e., lower cost per unit), decreasing labor costs, and saving on physical space.

Firms said they adopted advanced technologies as a way of reducing operational costs—including labor costs—to increase competitiveness and profitability. Some officials also specifically identified the pressure of

large low-cost competitors, both in the United States and globally, as a major motivation to reduce costs and product prices.

- Officials at a medium-sized door manufacturer told us that increased use of advanced technologies, such as robots, enabled the firm to increase efficiency, reduce labor costs, and re-focus its product line on custom doors to survive the entry of manufacturers in China that could sell mass-produced doors for lower prices.
- The original motivation for adopting robots at a medium-sized automotive parts manufacturer was a customer's price demand that the firm could not meet and still remain profitable, according to officials. Integrating more robots enabled the firm to reduce production costs by using fewer workers.
- At a large manufacturing corporation of household and personal care goods, officials told us the company had a goal of reducing its workforce size by 1,500 full-time positions per year for 5 years (across its subsidiaries), and specifically using robotic automation to accomplish 40 percent of its reduction goal.
- The constant pressure to keep costs low in the health care sector motivated a university-affiliated medical center we visited to explore adopting more advanced technologies, such as autonomous mobile robots that could decrease expenses by reducing the number of positions in some departments.

Firm officials also told us about other, non-labor-related cost savings considerations that led to the adoption of advanced technologies.

- Officials at a large automotive manufacturer told us they recently upgraded a laser welding system to use fewer, more advanced robots to save production line space—which is a valuable commodity in manufacturing. They also pursued this change to increase overall production capacity because the physical space they saved could be used to install more robots for other production steps.
- The integration of autonomous mobile robots to deliver prescription drugs to patient wards at a university-affiliated medical center was intended, in part, to save costs related to medicines that go missing when delivered and processed manually, according to officials.

Job Quality and Worker Safety

According to officials at selected firms, the desire to improve jobs led firms to adopt advanced technologies. The firms wanted to automate tasks that are dangerous, difficult, dull, or dirty in large part to improve worker safety, and to optimize the value added by workers. For example:

- **Dangerous work:** Two robots were installed to pick up doors weighing between 90 and 300 pounds, and place them on a paint line at a medium-sized door manufacturer we visited. Prior to the robots, workers who performed this dangerous task experienced work related injuries, and the firm paid large amounts of money in workers' compensation claims, according to officials. Once the robots were installed, the firm experienced a decrease in the number of worker compensation claims.
- **Dull work:** A small automotive parts manufacturer we visited installed an industrial robot to perform a machine-to-machine transfer of a heavy part. Prior to the robot, the firm had three workers performing this task—even though the task only required two—because workers would eventually quit due to the tedium of the job and new workers would require time to be trained, according to officials.
- **Value-added work:** Some officials told us they adopted advanced technologies because they wanted to maximize human labor that provided value to the firm and reduce labor that did not. Officials at a warehouse for a regional grocery store chain and a university-affiliated medical center said they wanted to minimize time workers spent traveling between tasks (as opposed to performing tasks). Warehouse officials said their workers spend up to 60 percent of their time traveling back and forth between shelves and products, which is time that could be spent selecting and sorting items. Thus, at the time of our visit, the warehouse was in the early stages of adopting automated guided vehicles to eliminate the need for workers to travel between points. Similarly, officials at a university-affiliated medical center that adopted autonomous mobile robots to transport, among other things, prescription drugs, said nurses and pharmacy technicians used to walk back and forth between the patient ward and the pharmacy to pick up and deliver these drugs, which diverted them from performing other tasks. They said that the medical center wanted them to have more time to provide valuable work, especially for employees who are highly-paid.

Recruitment and Retention

Officials at many firms said that adopting advanced technologies can help them deal with the challenges of recruiting and retaining skilled workers. They explained that worker shortages and high turnover can result from skill gaps in the local or national workforce, low unemployment, and

certain work being viewed as unappealing, among other reasons. For example, officials at a warehouse for a regional grocery store chain we visited told us they struggle with high worker turnover and the constant need to hire new workers. In addition, low unemployment can make it difficult to retain workers with the right skills to operate machinery according to officials at a small automotive parts manufacturer. Similarly, at the university-affiliated medical center, an official said that positions for pharmacy and other types of medical technicians can be difficult to fill. By using autonomous mobile robots to automate some tasks, the medical center can streamline its operations to more efficiently use the technicians it already has.

Recruitment in Manufacturing

Officials at some manufacturing firms we visited said they have had trouble attracting new workers into the sector, and officials at two firms said that adopting advanced technologies is one way they have sought to make manufacturing more attractive and to appeal to more and younger workers. One younger worker at a small automotive parts manufacturer talked about how appealing his workplace was due to the firm's use of advanced technologies, specifically robots. Officials at a large automotive manufacturer viewed their tech development facility, which includes spaces to tinker with virtual reality, augmented reality (i.e., technology that superimposes images on a user's view of the real world; for example, by wearing augmented reality glasses), and other emerging technologies, as an asset to recruit young talent.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

Product-Related Motivations

Improving product quality, expanding product offerings, and supply chain reliability were primary motivations for adopting advanced technologies, according to officials at some firms.

- **Product quality:** Quality is paramount in the automotive industry, where mistakes are costly and can have implications for a firm's reputation, according to officials at a medium-sized automotive parts manufacturer we visited. For this reason, they decided to use robots rather than workers for welding in order to standardize the processes, reduce errors, and improve product consistency and quality. Officials at a large automotive manufacturer similarly said that the firm has pursued machine learning technologies to ensure fewer defects and problems in vehicles. Engineers at the firm are developing a smart watch for workers who connect wires that will provide feedback to these workers if a proper connection is not made, based on the sound of the connection. The firm is already using machine vision technology that inspects vehicles as they pass through a section of the production line to ensure the correct pieces have been used for each vehicle model.

- **Expanding product offerings:** At a medium-sized fruit processing plant, an official said that integrating robots, an advanced conveyer system, and machine vision inspection technologies, among other advanced technologies, enabled the firm to begin producing applesauce in a highly automated and safe way. Had manual production been the only option, officials said they would not have considered producing applesauce due, in part, to safety issues.
- **Supply chain reliability:** One small manufacturer of rubber stamps and embossing seals (hereafter referred to as a small stamp manufacturer) used to rely on a single supplier for pre-cut materials, which was not always reliable. The firm adopted a collaborative robot, in part, so it could purchase raw materials directly and then have the robot cut the materials as part of the production process (see fig. 6).

Figure 6: Collaborative Robot Lifting Piece of Wood Prior to Cutting



Source: A small manufacturer of rubber stamps and embossing seals. © 2018 the stamp manufacturer. | GAO-19-257

Selected Firms Cited
Various Risks with
Adopting Advanced
Technologies, Such as the
Reliability of Technology,
and Working with New
Tech Developers

Reliability of Technology

In addition to the capital cost of advanced technologies, which some firms told us can be substantial, firms face a number of risks that can affect their return on investment, such as the reliability of technology and working with new tech developers.⁶⁹ While the firms we met with had already adopted advanced technologies, officials had to consider and overcome various risks during the adoption process. Some of these firms decided against adopting other advanced technologies upon evaluating these risks.

Being an early adopter of a technology is risky because the new technology may not yet be sufficiently reliable for firms' operations. Officials at a large appliance manufacturer we visited showed us technology that was supposed to use machine vision to autonomously inspect the wire connections for clothes dryers. They told us that the vision technology had been ineffective, so they took it off the production line for engineers to continue working with it in the lab; they planned to bring the technology back onto the line a few weeks after our visit. Officials at this firm said that the vision technology was still relatively immature, as it had a limited field of vision and yielded numerous false readings. Similarly, a warehouse we visited that invested in automated guided vehicles used them to move pallets for a short time, but then put them into storage because these vehicles did not have mature enough machine learning and vision capabilities for the firm's purposes. Eventually, officials from this warehouse began working closely with the developer firm to improve the vehicle technology, which advanced enough that it could be used. For instance, officials from the warehouse suggested adding turn signals to the vehicles to alert nearby workers of intended movements and improving the vehicles' ability to travel over spills without triggering the system's sensors to shut down.

⁶⁹ As private sector firms in the United States are generally profit-maximizing entities, firm officials who are acting with that goal in mind will make decisions to maximize their return on investment. As a result, if the risks of adopting an advanced technology are too great and will not yield enough return on investment, officials will not adopt the advanced technology. On the other hand, if the potential benefits outweigh those risks, the firm will adopt the technology.

Firm Size Might Affect Risk Tolerance

An official at one small manufacturing firm stated that larger firms may be more willing to be early adopters of technology, as they may be able to absorb the high risks of experimenting with expensive technologies, while smaller firms tend to wait until a technology has been optimized before deciding to adopt it. Accordingly, his firm only purchases industrial robots from an established manufacturer, although it would like to experiment with newer technologies in the future, such as augmented reality.

Officials at a large manufacturing firm told us they have purchased a number of advanced technologies to experiment with, even though they do not know yet how the technologies may ultimately be used in their production process. This firm also has teams of technicians and engineers who can adapt the technology for operations. During our visit, we met with engineers who demonstrated different potential applications of technologies that are still being tested, including using virtual reality to test new part design and augmented reality glasses to provide interactive training to workers.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

Officials at some firms explained that installing advanced technologies at times necessitated building manual redundancies into their operations due to reliability concerns. Officials at a construction consulting company and a municipal township that adopted a machine learning technology to inspect roads said the technology would miscategorize road quality at times, such as identifying tree branch shadows on the road as pavement cracks. While working with the developer to improve the technology, officials said they continued to conduct redundant manual inspections to ensure they were making road repair decisions based on accurate information. During our visit to a large appliance manufacturer, we saw multiple collaborative robots that were not working properly. As a result, workers were performing these tasks manually while the robots were down; officials told us that each of the firm's automated processes has workers trained to perform the tasks in case a technology was not working properly.

Technologies Viewed Differently by Firms

Some firms find a technology to be useful while others find little practical application for that technology, as illustrated by the various opinions firm officials had about collaborative robots.

Officials at one small manufacturer we visited said that a collaborative robot was well suited for the firm's production process and environment because, among other reasons: (1) the firm produces small durable goods that require dexterity rather than speed, which the collaborative robot could provide; (2) the collaborative robot would be safe around workers and could be trained by non-technical staff, so the firm's small workforce could adapt to its use; and (3) the collaborative robot could fit in the firm's limited floor space, as it would not require a cage.

On the other hand, officials at other manufacturing firms we visited told us that collaborative robots were less useful in their settings because they have significant weight and speed limitations in order to be safe enough to operate outside of a cage, limiting their usefulness for their firms.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

Working with New Tech Developers

Some firm officials told us it could be risky to work with tech developers with limited experience. Officials at a large appliance manufacturer said that newer developers may go out of business or be bought out by a larger firm, which could render the technology acquired from them obsolete (especially in terms of future servicing of parts and software updates). The officials stated that emerging technologies, both hardware and software, tend to not be standardized, so investing in a developer likely means investing in a type of technology that may not be supported by other developers if issues arise. We heard from some firms that they purchased technology from developers who already had established reputations and longevity. For example, a small manufacturer of durable goods selected a robotics company because of the founder's reputation and track record, among other reasons.

Other Risks

Operational slowdowns: The time period between initial adoption and optimization of a technology varies widely and can sometimes be a lengthy and ongoing process, according to officials.

- One small stamp manufacturer experienced a lengthy and iterative implementation process for an off-the-shelf collaborative robot they purchased. For example, they had to construct a customized environment for the robot to function in, make parts by hand, purchase a 3-D printer to develop tools for the robot, and build additional parts to take care of increased byproducts like sawdust.
- Officials at a large automotive manufacturer told us that new technology, such as machine vision technology used for automated

inspections, is often integrated on the weekends or during off-shifts. Then, on the first day of production after the new technology is integrated, the production line starts slowly and speeds up as worker comfort and experience increases.

- Outside of manufacturing, a consultant that helps facilitate the adoption of advanced technologies at firms said that firms' existing, or legacy, computer infrastructure can be a barrier to integrating machine learning technology, increasing complexity and causing an extended implementation process as his firm integrates the new technology platform with the legacy infrastructure.

Worker concerns: Officials at some manufacturing firms said they have encountered worker concerns with advanced technologies, and have employed various tactics to mitigate this, such as introducing workers to the technology in offsite demonstrations and involving them during the decision-making and planning before the technology was integrated. In one case, workers were able to ask questions about a collaborative robot as it was being installed and were provided with orientation training. The robot was then phased into operations—used initially for short periods of time so workers would become accustomed to its physical presence and proximity to their workstations.

Deciding Not to Adopt Advanced Technologies

Officials at the firms we visited identified instances in which they chose not to adopt certain advanced technologies, or not to use advanced technologies that were working well in other processes. Reasons we heard included:

- a product line had too much variation to benefit from advanced technologies (i.e., that some advanced technologies work better for standardized products and processes);
- a certain manufacturing process was too low-volume to invest time and resources into automation; and
- human dexterity is difficult to replicate.

Officials from a large appliance manufacturer showed us an instance where using automation would not make sense. We observed a worker performing a simple, single task: grabbing a metal heat shield and plastic dishwasher spinner from separate bins and clipping one on to the other. Because of the shape of the pieces and because they were lying unorganized in boxes, the task requires human dexterity, making the process difficult to automate, according to officials.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

Adopting Advanced Technologies Has Had Varied Effects on the Workforces of Selected Firms, Including Declines in Some Types of Work and Gains in Others

Officials Said Advanced Technologies Have Replaced Positions at Some Selected Firms, and Most Firms Relied on Redeployment of Workers and Attrition Rather than Direct Layoffs

Officials at many of the firms we visited said they needed fewer workers in certain positions after adopting advanced technologies to perform tasks previously done by workers.⁷⁰ Officials at these firms generally told us they adjusted by redeploying workers to other responsibilities and, in certain instances, reducing the firm's workforce size through attrition. We also heard examples of direct layoffs due to the adoption of technologies. There may also be other types of adjustments firms can make that we did not observe or discuss with these officials. The complexity of these workforce adjustments makes it difficult to determine or measure the effects of technology adoption on workers. For example, although workers may not have lost their jobs due to an adopted technology taking over specified work tasks—either because of redeployments or attrition—fewer job opportunities might be available in the future for workers with similar skills. In addition, the iterative and sometimes lengthy process of incorporating advanced technologies can delay workforce effects. Thus, the absence of short-term effects of technology adoption does not necessarily preclude long-term implications, such as reductions or slower growth rates in workforce size over time (see text box below). As discussed in the prior section, one reason firm officials are motivated to use advanced technologies is to decrease labor costs.

⁷⁰ Not all technology adoption resulted in clear workforce effects. As discussed in the prior section, some advanced technologies are still being tested for reliability, so workforce effects could materialize at a later point in time.

Slower Workforce Growth than Revenue Growth

An official from a small automotive parts manufacturer told us that advanced technologies and automation resulted in revenue increasing by more than 400 percent over the last 12 years while the workforce increased about 15 percent. Production workers now make up a smaller percentage of the overall firm workforce than prior to automation, and sales and support staff now make up a greater percentage. The firm official described this change as an increase in higher-skilled jobs and a decrease in lower-skilled jobs.

Similarly, according to firm officials at a different medium-sized automotive parts manufacturer, revenue has grown six times in the past 15 years while the workforce has grown four times, largely as a result of adopting robotics technology.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

Redeployments without job loss: When advanced technologies replaced positions, firms we visited often shifted, or redeployed, workers to different responsibilities. For example, officials at a medium-sized automotive parts manufacturer we visited told us they had nine workers who smoothed sharp edges and removed burrs on hydraulic cylinders prior to installing two robots to perform these tasks. Now, with the robots in these positions, three workers load the robots and then inspect and deburr any parts of the cylinders the robots missed. The other six workers were redeployed to other tasks, according to a firm official. At a large appliance manufacturer we visited, officials told us that two workers used to move large parts from one line to another line to be painted. Now, as we observed, a collaborative robot performs this function alone; a worker monitors the operation to ensure it is running smoothly, and the original workers were moved to different tasks on the production line, according to officials. Although the size of these firms' workforces did not decrease as a result of the technology adoption, the numbers of certain positions were adjusted—for example, production positions decreased while monitoring positions increased. Differences in skills required for these positions may also affect the ability of current workers to transition and could have implications for individual workers even though the number of jobs at the firm does not change. These sorts of changes may or may not appear in firms' reported employment data, depending on whether redeployed workers change occupations or what other workforce changes may be occurring simultaneously (e.g., if other production workers are hired for reasons unrelated to the technology adoption).

Redeployments with job loss through attrition: Officials at some of the selected firms that redeployed workers said they also reduced their overall workforce size through attrition, as a result of adopting advanced technologies.

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- Autonomous mobile robots independently transported biohazardous waste, linens, meals, and prescription drugs throughout the university-affiliated medical center we visited. Officials told us they eliminated 17 positions after they deployed the robots. No workers were laid off; instead, they relied on high staff turnover rates and moved workers to vacant positions elsewhere.
 - At a medium-sized fruit processing plant, firm officials told us they replaced 150 to 200 jobs with various advanced technologies over the past 3 to 4 years. However, they relied on attrition rather than layoffs. For example, the plant adopted a robot to pack food into boxes. Prior to using the robot, officials told us there were 26 workers per shift performing this job; as of our visit, there were 13 workers per shift.
 - A medium-sized door manufacturer reduced its workforce from 650 employees to less than 500 over approximately the last 20 years due to, among other things, their adoption of robots, according to firm officials. For example, we observed industrial robots that load steel sheets into a cutting machine, reading a barcode on each sheet that tells them what size sheet is being lifted and how it should be placed in the cutting machine. This process only requires a single worker to monitor the robots during each of two shifts, where previously three workers per shift were on this production step (i.e., a change from six to two workers total).

How quickly workforce reductions materialize for firms using attrition can vary greatly. We visited firms with low employee turnover rates and firms with high turnover rates. High worker turnover rates allowed some firms to more quickly adjust their workforces when deploying advanced technologies and may be a reason we were told about job loss through attrition rather than layoffs at these firms.

Job loss through layoffs: An official from a systems integrator firm (“integrator”) provided examples of significant layoffs as a direct result of advanced technologies. This integrator provides machine learning technology and other similar products to automate office and administrative processes, among other things. One of the integrator’s customers—a U.S. automotive parts firm facing competition from online retailers—adopted machine learning technology to take over its accounts payable and distribution system. As a result, according to the integrator’s official, this firm reduced the number of employees in one of its U.S. offices from 500 to 200. Another of this same integrator’s customers—a firm that sells telecommunication circuits—adopted machine learning technology to automate product returns processing. As a result, the firm

experienced a 30 percent reduction in customer care calls, and replaced about 150 jobs in a U.S. call center with 110 jobs at a call center in a different country (i.e., about 150 U.S. jobs lost; and an overall workforce reduction), according to the integrator’s official.

Advanced Technologies Helped Increase Competitiveness and Enabled Employment Growth Despite Positions Being Replaced, According to Officials at Some Selected Firms

Productivity and Efficiency Gains

Adopting advanced technologies has helped some firms improve their product quality and increase their production efficiency.

For example, according to officials at a medium-sized fruit processing plant, after the firm began using an automated fruit grading technology, the process took significantly less time and resulted in far fewer complaints from farmers about the grading. Farmers thought the automated grading technology was fairer and more accurate than having workers manually and subjectively grade the fruit.

A large appliance manufacturer that began using a collaborative robot to apply sealant to an appliance door observed improved consistency, which led to fewer service calls from retailers and customers about excessive, insufficient, or incorrect seals.

One medium-sized door manufacturer said that automation technologies enabled them to produce and ship doors in 3 days, as opposed to 4 to 6 weeks.

An official from a warehouse for a regional chain of grocery stores said that using automated guided vehicles allowed the firm to save time moving pallets from one end of the warehouse to the other, and also save worker hours. The warehouse saves just over \$2 per pallet moved by an automated guided vehicle rather than a worker, and up to \$3,500 a day based on volume, according to the official.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

According to officials at some selected firms, greater competitiveness and productivity due to the adoption of advanced technologies (see sidebar) has helped firms grow their workforces. For example, some hired additional production workers due to increased production (despite some production tasks being taken on by the adopted technologies), or new types of workers, such as technicians to maintain the technologies. Some officials also said that although they may not have grown their workforces, adopting advanced technologies helped them stay in business by allowing them to compete effectively, and thus to preserve jobs and retain workers. For example, officials at a medium-sized door manufacturer, where we observed numerous robots in the production facility, told us that their firm “could not survive” global competition without the use of advanced technologies.

Advanced technologies enabled some selected firms to increase production or produce a larger range of goods, and thus to hire additional production workers. This also led to workforce increases for suppliers and other firms, according to officials.

- One large appliance manufacturer increased its use of robots and other advanced technologies to produce more of its own component parts internally instead of relying on suppliers. As a result, the firm was also able to increase the number of production jobs, according to firm officials.
- Due to advanced technologies, a small automotive parts manufacturer was able to bid on a contract to produce a new and more intricate part for a major automotive manufacturer. An official described how the part was so intricate that it could not have been produced manually with the required level of consistency and speed. Although the firm adopted six robots to produce this part, winning the contract also created nine new jobs. While the robots are completing much of the production, the volume of parts demanded and the existence of some tasks that only workers can complete has led to this job growth.
- A developer of autonomous mobile robots said that, as a result of increased business, his firm has created jobs among its eight local suppliers where he buys parts, such as motherboards for the robots.

Growth of Developer and Integrator Firms

Selected developer firms we met with said they grew their technical and non-technical staff as a result of increasing demand for their technologies.

- A firm that develops and produces robots had tripled its workforce size, to about 130 employees, in the last year alone, according to officials.
- An official at another developer firm that makes inspection robots said they had grown from three workers to about 20 and envisions expanding to 100 in the near future. The official said that the firm's first years were spent on technology development, but that once the technology was deployable to customers, the firm grew its workforce size.

Integrator firms that help companies adopt advanced technologies have also grown in size, and new types have emerged, according to integrators we visited. For example, with the development of smarter robots, one integrator firm we visited entered the industry to recondition and sell old robots; the firm also adds newer technology to these robots if requested. This integrator has grown from 35 to 45 employees in the last 10 years, according to officials, with the new positions being primarily robot technician jobs.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

As a result of technology adoption, some firms hired more workers with technical skills, and in other instances lower-skilled workers, according to firm officials.

- An official from a warehouse for a regional chain of grocery stores said that adopting an advanced automation system created a need for three additional workers to provide preventive maintenance on the machines. These additional positions pay about 25 percent more than the standard warehouse positions, according to officials.
- At a large automotive manufacturer, officials told us the firm increased its number of lower-skilled cleaning jobs when robots began producing large amounts of byproduct.

Officials Said Workers' Roles, Tasks, and Skills Have Been Changing Due to Advanced Technologies at Selected Firms

At the firms we visited, workers changed roles and tasks as a result of advanced technology adoption, such as focusing more on interactive, cognitive, higher-skilled, and monitoring tasks, and in other cases focusing more on lower-skilled tasks. Workers who can adapt and be flexible to task changes may experience positive effects, including work that is less physically taxing, safer, more ergonomic, less monotonous, or higher paying. On the other hand, workers who are unable to adjust to changing tasks may be negatively affected. Officials at some of the firms told us that their firms provided internal training or leveraged external resources to develop workers' skills to help them move into new positions. During our visits to selected firms, we saw a variety of ways in which tasks for workers are changing.

Interactive work: The use of autonomous mobile robots to deliver prescription drugs for patients enabled nurses at the university-affiliated medical center we visited to focus more of their time on patient interaction, according to officials. The small stamp manufacturer we visited would like to continue to automate its ordering process and focus more on providing customer service. Officials there said for future hires, they plan to recruit for data and people skills, rather than production skills.

Cognitive work: A federal statistical agency adopted machine learning technology to automatically interpret text narratives on forms and assign codes to the data. As a result, staff who previously entered this information manually are able to spend more time on analytical tasks such as reviewing the accuracy of the auto-coding, correcting issues, obtaining clarifications about information submitted on the forms, and following up with non-respondents, according to officials.

Higher-skilled work: At a large automotive manufacturer, due to increased use of advanced technologies, workers who are hired today need to have greater technical proficiencies than workers hired in the past. For example, to adapt to their changing roles working with robotic equipment, non-technical production staff need machine maintenance and technical skills, rather than only manual dexterity skills. Officials at a large appliance manufacturer that adopted an automated machine to stamp metal said that the resulting process required a single worker to monitor the machine and provide basic maintenance. This worker needed technical skills and at least 6 months of training to effectively perform these duties. In contrast, at another one of this firm's global plants, four separate pressers are used and each requires workers to load and unload metal.

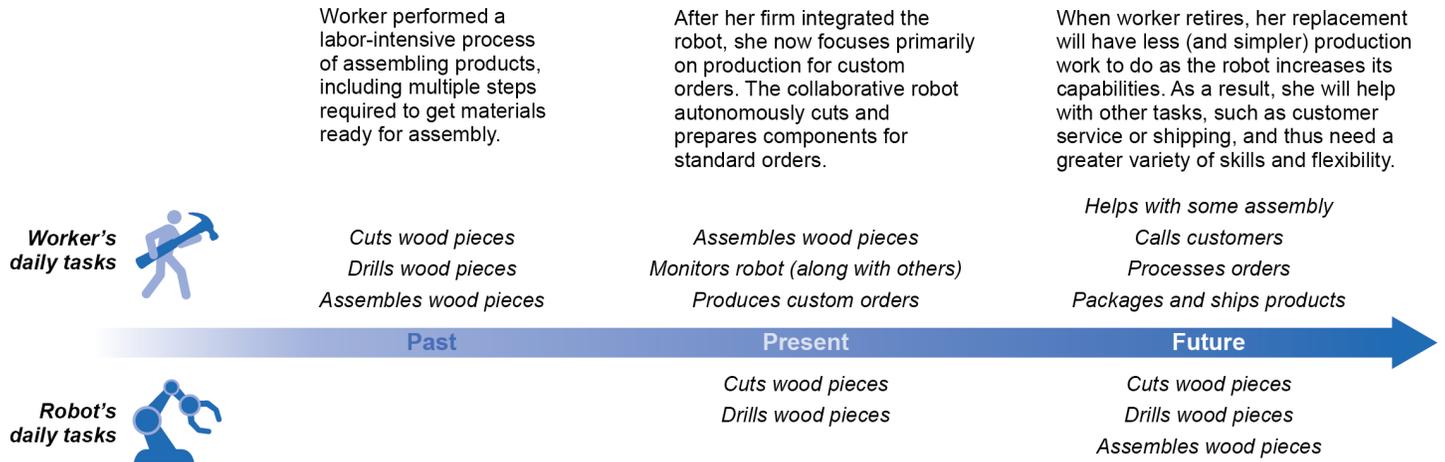
Monitoring work: Officials at the large appliance manufacturer mentioned above showed us a step in their production process in which two small pieces of plastic and metal need to be attached. Three workers used to perform this task by hand, which caused ergonomic challenges, and inconsistencies in both quality and production cycle times. Now, the firm uses three robots to perform this work and a single worker loads the pieces for all three robots and monitors their performance. At a small automotive parts manufacturer, production operators who work in cells with robots monitor multiple machines and sometimes also monitor multiple work cells, so a greater aptitude level is needed. As a result, these operators earn \$3 per hour more than operators in work cells without robots, according to a firm official.

Less physically taxing work: Staff at some firms also told us how advanced technologies have made worker tasks less physically demanding. For example, we talked with one warehouse worker who used to lift heavy boxes, but who now operates a forklift after his old task was automated with a conveyer belt and sorting system. He described his new position as having ergonomic benefits, including experiencing less back pain. At a large automotive manufacturer, officials said the firm installed six robots to paint vehicle interiors. This production step was a major ergonomic hazard and workers who did this painting had a relatively high injury rate, according to officials. Officials told us that adopting the robots lowered the injury rate among these workers and resulted in faster vehicle painting.

Simplified work: At a small stamp manufacturer that adopted a collaborative robot, officials told us that as the firm continues to redesign and optimize operations, the robot will take on more complex tasks. As a result, the remaining production work performed by the firm's production worker will be simpler (see fig. 7). Officials said that in the future, after the firm's current production worker retires, the firm may rely on contingent workers to perform any needed production work not completed by the robot because the tasks will be simpler and easier to train a new, temporary worker to complete. Officials said the firm may also hire a worker with a different and more varied skillset who can perform the few remaining production tasks along with other types of tasks.

Figure 7: Illustration of Changes to a Worker's Tasks After a Selected Firm Integrated a Collaborative Robot

A small manufacturer of durable goods told us about the impact of a robot on their lone production worker, who had been with the firm for decades.



Source: GAO analysis of discussions with firm officials during a visit to a small manufacturer of rubber stamps and embossing seals. | GAO-19-257

Notes: Collaborative robots are designed for direct interaction with humans within a defined collaborative workspace with certain safety standards required, according to the Robotic Industries Association. The collaborative robot we observed at the small manufacturer of durable goods consisted of, among other things, a robot arm that picked up and moved wood pieces around and cut them with a sawblade. Officials told us that the robot would stop immediately if it met an unexpected obstruction, such as bumping a human coworker.

Lower-skilled work: Officials at a medium-sized door manufacturer installed a robot to facilitate the firm's redesigned door sealant system and production process. The original process of manually applying door sealant was physically-intensive, ergonomically challenging, and required significant skill and experience to precisely apply the sealant. With the new design, a robot applies the sealant autonomously. As a result, workers perform lower-skilled tasks in this process, including placing a piece on a platform, visually inspecting the robot's work, cleaning and setting up the robot's work station, and confirming the correct program is entered in the computer.

Adaptability to changing daily work demands: Officials from selected firms told us that due to advanced technology adoption, workers need to change tasks depending on the day and circumstances. For example, at a large appliance manufacturer some workers serve in different capacities depending if the robots are functioning properly and depending on the production needs of that day. On the day we visited the plant, several of the robots were malfunctioning and workers were performing the robots'

tasks. Firm officials said that some of their workers serve in swing roles and move around to different production processes and assist as needed.

Training

Training Centers for Advanced Tech Skills

We met with officials at a training center that re-trains adults and teaches high school students to work with advanced technologies used in manufacturing. We visited two firms in the area that told us that this training center helps fill a local shortage in maintenance technician skills, and that they have hired workers who graduated from the center.

Officials at the training center said that there is a high demand in the area for maintenance technicians. For example, they said that a large automotive manufacturer in the area is planning to hire 800 maintenance technicians over the next 3 years, and that the firm is worried about how it will fill these positions. Officials at the training center also said that some firms have such a high demand for maintenance technicians that they hire high school students who complete the training program before they graduate high school.

The training center is piloting its adult training program. The program recruits adults who are underemployed and have some mechanical aptitude, then trains them in advanced technologies used in manufacturing. Most of the students who participated in an early pilot obtained higher paying jobs than those they held before the program, according to officials at the training center.

Source: GAO analysis of interviews with firm officials. | GAO-19-257

Many firms we visited offered training for workers to adapt to their changing roles and tasks, particularly when the tasks or roles became more technical. Some firms used internal training resources and some leveraged local training centers (see sidebar). Some technology developers also offered training to firms that adopted their technologies. Officials at some firms told us that training current workers for more technical positions was easier than finding workers with the appropriate skills. For example, officials at one medium-sized door manufacturer said they needed highly specialized engineers, but could not find any in the region. As a result, this firm offered tuition reimbursement for workers who were willing to go back to school to become engineers. They also partnered with local community colleges to train students to become future maintenance technicians. Officials at a large automotive manufacturer said that due to increases in the firm's use of advanced technologies, the plant has needed to hire more technicians. As a result, this firm added programs to its on-site training center to train workers for these roles.

Conclusions

The complex job changes we observed at the selected firms we visited are not currently captured in federal data, though they may have significant implications for broader employment shifts. As the primary agencies responsible for monitoring the U.S. economy and workforce, the Departments of Commerce and Labor are aware of the importance of advanced technologies as major drivers of changes. For example, Census' newly administered Annual Business Survey may provide valuable information in the future about the adoption and use of advanced technologies nationwide and the prevalence of resulting workforce effects. However, comprehensive data on firms' adoption and use of advanced technologies do not currently exist, which prevents federal agencies and others from fully monitoring the spread of advanced technologies throughout the economy and linking their use to changes in employment levels or structural shifts in the tasks and skills associated with jobs.

Observations from our visits to selected firms illustrate the complex and varied workforce effects that result from firms' adoption of advanced technologies. In some circumstances, technology adoption will lead to increases in different types of jobs and in other cases technology adoption will lead to workforce reductions—either over time or immediately. Regardless of the firm-level workforce effects, worker roles and responsibilities are likely to change as advanced technologies take over tasks that workers previously performed. These changes could positively affect some workers, but could also have negative consequences for other workers, especially those who are unable to adapt to changes. For example, workers whose previous work tasks are automated and who are unable to perform new tasks required of them may need to seek new employment. If these changes occur occupation-wide, across many firms, workers may need to re-train or seek new employment in entirely different occupations or industries. To the extent that these changes are concentrated among occupations susceptible to automation, certain groups of workers (e.g., those with lower education levels) may be disproportionately affected and may lack the opportunity to develop skills needed to enter growing occupations. These workers will be in greater need of programmatic or policy supports, and federal workforce programs will need to be aligned with in-demand skills for the changing economy.

Without comprehensive data that can measure the magnitude and variety of these firm-level changes, the workforce effects of the adoption of advanced technologies will remain unclear, job seekers may not be fully

informed about their best future career prospects, and federally funded programs to support workers may be misaligned with labor market realities. DOL's ability to collect information regularly on jobs and workers may enable the agency to fill these information gaps. Specifically, better data could be used by policymakers and DOL to proactively design and fund worker training programs that meet the job needs of the future.

Recommendation for Executive Action

The Secretary of Labor should direct the Bureau of Labor Statistics (BLS) and the Employment and Training Administration (ETA) to develop ways to use existing or new data collection efforts to identify and systematically track the workforce effects of advanced technologies. For example, the Secretary could select any of the following possibilities, or could identify others.

- BLS could expand existing worker or firm surveys to ask respondents whether advanced technologies have resulted in worker displacements, work hour reductions, or substantial adjustments to work tasks.
- BLS could expand its employment projections work to regularly identify occupations projected to change over time due to advanced technologies.
- ETA could expand the O*NET data system to identify changes to skills, tasks, and tools associated with occupations, as the information is updated on its rotational basis, and consider how this could be used to track the spread of advanced technologies.

(Recommendation 1)

Agency Comments

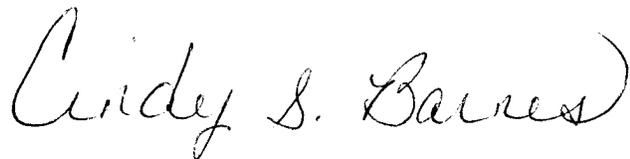
We provided a draft of this report to DOL, Commerce, NSF, and OSTP for review and comment. We received written comments from DOL that are reprinted in appendix II and summarized below. DOL and Commerce provided technical comments, which we incorporated as appropriate. NSF and OSTP told us that they had no comments on the draft report.

DOL agreed with our recommendation to develop ways to identify and track the workforce effects of advanced technologies. DOL stated that it will continue coordinating with the Census Bureau on research activities in this area, and that it plans to identify and recommend data collection options to fill gaps in existing information about how the workplace is affected by new technologies, automation, and AI. DOL also stated that it

plans to release employment projections annually instead of every 2 years, beginning in 2019.

As agreed with your offices, unless you publicly announce the contents of this report earlier, we plan no further distribution until 30 days from the report date. At that time, we will send copies to the appropriate congressional committees, the Secretary of Labor, the Secretary of Commerce, the Director of the National Science Foundation, the Director of the White House Office of Science and Technology Policy, and other interested parties. In addition, the report is available at no charge on the GAO website at <http://www.gao.gov>.

If you or your staff have any questions about this report, please contact me at (202) 512-7215 or brownbarnesc@gao.gov. Contact points for our Offices of Congressional Relations and Public Affairs may be found on the last page of this report. GAO staff who made key contributions to this report are listed in appendix III.



Cindy Brown Barnes, Director
Education, Workforce, and Income Security Issues

Appendix I: Objectives, Scope, and Methodology

The objectives of this review were to examine (1) what is known about how the adoption of advanced technologies affects the U.S. workforce; (2) selected federal agency efforts to track and monitor the adoption and workforce effects of advanced technologies; (3) considerations that led selected firms to adopt advanced technologies and the risks they faced; and (4) ways technology adoption has affected the workforce at selected firms.

Throughout the report, we use “advanced technologies” as a broad term to describe technological drivers of workforce changes, including but not limited to those identified in the National Academies study: artificial intelligence; machine learning; robotics; autonomous transport; advanced manufacturing; 3D printing; advanced materials; computing power; and internet and cloud technology.¹ The technologies we observed at work sites could generally be categorized as applications of robotics, machine learning (e.g., machine vision or autonomous navigation), or both. However, not all technologies that may affect the U.S. workforce in the future—through automation or in other substantial ways—fall into these categories. Our use of the broad term “advanced technologies” leaves open the possibility that new technologies and other areas of focus are likely to emerge.

To examine what is known about how the adoption of advanced technologies affects the U.S. workforce, we explored the extent to which available federal data could identify and measure these effects, and we identified limitations with available data. Because there was no comprehensive data that link employment trends to technology adoption, we used a study by Frey and Osborne to identify a group of occupations susceptible to automation.² We then analyzed whether the concentration of these occupations in industries is correlated with growth in tech jobs or employment declines in those industries, whether job displacements are more common in these occupations than in others, the characteristics of workers who hold jobs in these occupations, and the geographic concentration of jobs in these occupations. We analyzed employment data from the Census Bureau (Census) and the Bureau of Labor Statistics (BLS); specifically, the American Community Survey (ACS), the

¹ National Academies, *Information Technology and the U.S. Workforce* (2017).

² Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016). In developing their model, Frey and Osborne rely on data on tasks and employment as of 2010.

Current Population Survey's (CPS) Displaced Worker Supplement, and the Occupational Employment Statistics (OES) survey. For more information, see detailed discussions of our data analyses in sections 1-3 below.

Identifying occupations susceptible to automation: Using a model that evaluates tasks within an occupation, Frey and Osborne estimate a probability of automation for 702 occupations.³ They identify occupations with a probability greater than 0.7 as being at high risk of automation.⁴ In our analyses, we thus consider this collection of occupations as those susceptible to automation. While there are different studies that attempt to predict what occupations or jobs may be automated in the future, we use the work by Frey and Osborne because it is widely cited and because its results are structured to allow us to identify a broadly inclusive collection of occupations susceptible to automation. The results of our analyses could be affected by using other studies to the extent that they identify different occupations as susceptible to automation. The accuracy of any collection of occupations is limited by the unpredictability of when or if jobs are automated, as well as the fact that occupations are comprised of a variety of jobs, which may experience automation to varying degrees or in different ways.

We also reviewed examples of recent and ongoing studies that attempt to measure workforce effects directly attributable to technology adoption. We identified examples of research through interviews with knowledgeable individuals and from among those included in a recent review of the state of empirical work.⁵ Our review of studies was not meant to be comprehensive of the research in this area.

To identify selected federal agencies' current and planned efforts to collect data on, and monitor the prevalence and effects of advanced technologies in the economy, we met with the Departments of Labor (DOL) and Commerce (Commerce), as the principal federal agencies responsible for collecting data on the U.S. economy and workforce; the White House Office of Science and Technology Policy (OSTP), which leads interagency science and technology policy-coordination efforts

³ Frey and Osborne analyzed occupations using data on work tasks as of 2010.

⁴ Probabilities range from 0 to 1, or no chance of automation to a 100 percent chance of automation.

⁵ Raj and Seamans, "AI, Labor, Productivity and the Need for Firm-Level Data."

across federal agencies; and the National Science Foundation (NSF), which was involved in the development of the Annual Business Survey. We interviewed officials and reviewed data and information collected by these agencies. We also reviewed the Annual Business Survey's questionnaire to consider the potential uses of data being collected by the survey, and analyzed data from DOL's Employment Projections program and Occupational Information Network (O*NET) database to identify information related to the adoption and workforce effects of advanced technologies.

- **Annual Business Survey:** The Annual Business Survey was administered for the first time in summer 2018, and collects information from firms about various topics, including innovation and technology use. The survey is a joint effort by the Census Bureau and the National Center for Science and Engineering Statistics within the National Science Foundation and Census plans to administer the survey annually for 5 years. The Annual Business Survey replaces the 5-year Survey of Business Owners, the Annual Survey of Entrepreneurs, the Business R&D and Innovation for Microbusinesses survey, and the innovation section of the Business R&D and Innovation Survey.
- **Employment Projections program:** BLS's Employment Projections program analyzes changes in the economy, among other things, to project how employment by occupation may change over the next 10 years, including which occupations may be affected by advanced technologies.⁶ BLS's projections are for the most part structured around the Occupational Employment Statistics, which produces employment and wage estimates for over 800 occupations.⁷ As part of this program, BLS develops a table of occupations that are projected

⁶ Every 2 years, BLS publishes 10-year projections of national employment by industry and occupation. According to BLS officials, research to develop occupational projections includes reviews of literature and economic studies, outreach to experts, industry contacts, and trade associations, and also quantitative analysis of historical OES employment data.

⁷ Self-employed workers, workers employed by private households, and most agricultural workers are not included in the OES survey, though these workers account for a small share of total employment, according to BLS. BLS uses Current Population Survey data for employment projections for these groups; these data use a different occupation classification than the OES survey.

to have direct employment changes due to some identified reason.⁸ According to BLS officials, the specific reason listed for each occupation is based on BLS's judgment of the most significant factor or factors affecting the occupation (i.e., based on a qualitative assessment). We examined the reasons listed in this table and identified those related to the adoption of advanced technologies in an occupation, such as through automation, the increased use of robots or artificial intelligence, advances in machine or software technologies, or other similar changes. We then counted the number of unique occupations projected to experience declines in their shares of employment in an industry or group of industries due to one of these reasons. We also counted these occupations according to their major occupation group. BLS projected that some of these occupations would experience employment share declines in all industries and some would experience employment share declines in a single industry only. We counted unique occupations regardless of what industries or how many were noted (e.g., all industries or only one). We chose to do this to capture an inclusive list of occupations projected to be affected by advanced technologies, and because we are not using the list to quantify total projected employment changes. Of the 247 unique occupations BLS includes in its table as projected to have direct employment changes due to some identified reason, BLS projects that 163 will experience employment share declines—100 of those occupations are projected to change broadly as a result of the adoption of advanced technologies.⁹ An employment share

⁸ Bureau of Labor Statistics, *Table 5.1: Factors Affecting Occupational Utilization, Projected 2016–26*, Employment Projections program, accessed November 5, 2018, <https://www.bls.gov/emp/tables/factors-affecting-occupational-utilization.htm>. *Table 5.1* only captures active staffing pattern changes, as opposed to downstream effects (i.e., automation in one occupation affecting employment in a different occupation), according to BLS officials. Overall projections are based on a combination of industry changes and staffing pattern changes. Not all occupations are included in *Table 5.1* because only staffing pattern changes are identified and discussed in this table and for many occupations, these are projected to remain unchanged, according to BLS. In addition, some staffing pattern changes are not reflected in this table because the information for a certain occupation is not publicly releasable. Some of the occupations in the table are projected to experience employment share increases.

⁹ Although these occupations could be used in our various analyses, because BLS identifies them based somewhat on qualitative judgment, we focused our analyses on the occupations identified by the Frey and Osborne study as susceptible to automation. As previously noted, the Frey and Osborne study is also widely cited. As a sensitivity test, we compared the occupations BLS projects will experience employment share declines broadly as a result of the adoption of advanced technologies to those occupations that Frey and Osborne identify as susceptible to automation—76 of the 100 occupations we identified in BLS's table were also identified by Frey and Osborne.

decline indicates that employment in an occupation will decline relative to others in a given industry or group of industries, not that the occupation will necessarily experience a decrease in employment in absolute terms.

- **Occupational Information Network (O*NET) database:** The O*NET database contains information about the skills, tasks, and tools (i.e., use of technology) associated with specific occupations.¹⁰ We downloaded two components of the database that (1) list the various work tasks associated with each occupation, and (2) list the various tools and technologies used by each occupation. In each database component, we searched for and identified tasks, tools, and technologies that involved robots in some way—e.g., tasks such as working with robots, robotic systems, or robotic applications, and tools such as welding robots, loading robots, or robot automation tools. We then counted the number of unique occupations that (1) had an associated work task related to robots, or (2) used a robot-related tool in the occupation.¹¹

To understand firms' adoption of advanced technologies and any resulting workforce effects, we met with officials representing 16 different firms that are using advanced technologies in their operations, as well as a systems integrator who provided detailed information about how several customer firms are using advanced technologies.¹² Most of the meetings with firms were in-person site visits; three of the meetings with firms and the meeting with the systems integrator were by phone. Throughout this report, we use the term "firm" for simplicity, although the "firms" we met with included production plants of large manufacturers, single-location firms, public sector agencies, and other entities (see below). We also identify the manufacturing firms we visited as falling into one of three

¹⁰ According to ETA officials, the primary purpose of O*NET is to assist job seekers in making employment decisions and it was not designed to track workforce effects or directly track occupational changes over time.

¹¹ To identify and count unique occupations that used a robot-related tool or technology, we examined both the tools and technologies in the database as well as the United Nations Standard Products and Services Code (UNSPSC) description associated with those tools and technologies. There were instances in which the tool or technology did not refer to robots but the UNSPSC description did. For example, the tool "computer-controlled welding equipment" was categorized as "welding robots" under the UNSPSC description. We thus identified this as a robot-related tool.

¹² We do not reveal the identity of the firms we met with, although we include some descriptive detail throughout the report on the type of firm our observations are from.

different size groups to describe their relative size differences from each other. The manufacturing firms we visited ranged from eight employees to thousands, according to firm officials. For the purposes of our study, we define small as fewer than 200 employees; medium as 200 employees to 1,000; and large as over 1,000 employees.

Among the 16 firms we met with that are using advanced technologies, 10 are manufacturing firms:

- a small manufacturer of rubber stamps and embossing seals (also referred to as a small stamp manufacturer);
- two medium-sized door manufacturers;
- a small automotive parts manufacturer;
- a medium-sized automotive parts manufacturer;
- two large appliance manufacturers;
- a large automotive manufacturer;
- a large manufacturing corporation of household and personal care goods; and
- a medium-sized fruit processing plant.

Six are non-manufacturing firms of various types:

- a construction consulting company;
- a federal statistical agency;
- a food retail corporation;
- a municipal township;
- a university-affiliated medical center; and
- a warehouse for a regional grocery store chain.

The firms about which we received information from the systems integrator were business, administrative, and customer relations offices of various firm types.

To identify firms to meet with, we consulted and sought referrals from a variety of knowledgeable sources, including academic researchers, technology developer firms, technology integrator firms, state economic development associations, and our own research. We selected firms that varied in size, industry sector, types of advanced technology used, and

geography.¹³ We limited our focus to firms that had adopted advanced technologies and had experienced workforce effects. Our selection of firms is not a generalizable sample, but does provide illustrative examples of the adoption and workforce effects of advanced technologies.

During our site visits at firms, we met with one or more management officials and, at times, with workers. We were also able to view the advanced technologies being used in operations. Our discussions with officials included topics such as motivations for adopting advanced technologies, the integration process, and any workforce effects that resulted from the technologies, including positions lost or gained and how workers' tasks and skills may have changed. Our site visits and interviews with firm officials ranged from hour-long conversations to full-day visits, so some site visits yielded more detailed information than others.

In addition to the firms that use advanced technologies, we interviewed seven technology developer firms and two robotics integrator firms (in addition to the systems integrator mentioned above). We met with these firms to learn more about some of the technologies being used and the adoption process, as well as about workforce effects at these firms. We identified these developer and integrator firms from various sources, including our conversations with academic researchers and our own research.

We conducted additional interviews to obtain background and context for our work. We met with individuals knowledgeable about issues related to the adoption and workforce effects of advanced technologies, such as academic researchers and economists, officials from two unions representing manufacturing workers, officials at three industry-based organizations, officials from two state economic development associations, and officials at two worker training centers. For all objectives, we also reviewed relevant federal laws and regulations.

The remainder of this appendix provides detailed information about the data and quantitative analysis methods we used to examine what is known about the workforce effects of automation and the adoption of advanced technologies (objective 1), as follows:

¹³ Although we selected multiple firms in relative proximity to each other to visit in-person, we met with firms located in six states and the District of Columbia, as well as some firms that operate in multiple states.

-
- **Section 1:** Analyses using data from the ACS
 - **Section 2:** Analyses using data from the CPS's Displaced Worker Supplement
 - **Section 3:** Analyses using data from the OES survey

For each of the datasets described below, we conducted a data reliability assessment of variables included in our analyses. We reviewed technical documentation and related publications and websites with information about the data. We spoke with BLS and Census officials who maintain the datasets to gain an understanding of and provide context for the various data that we analyzed, as well as to resolve any questions about the data and to identify any known limitations. We also tested the data, as applicable, to check for logical consistency, missing data, and consistency with data reported in technical documentation. We determined that the variables we used from the data we reviewed were sufficiently reliable for the purposes of this report.

Section 1: Analyses Using Data from the American Community Survey

This section describes the quantitative analysis methods we used to examine employment trend correlations and the characteristics and earnings of workers in occupations susceptible to automation (as identified by Frey and Osborne; see above). We used ACS data for these analyses.

The ACS is administered by the Census Bureau and is an ongoing national survey that uses a series of monthly samples to produce annually updated estimates for the same areas surveyed via the decennial census. The ACS collects a range of information about individuals from a large sample of households—over 2.2 million respondent households in 2016—including employment information such as occupation, industry, and earnings, and demographic information such as age, gender, race, ethnicity, and educational attainment. We limited our analysis to workers who were classified as current employees, and who had earned positive wage and salary income in the prior 12 months. In 2016, this resulted in observations representing 136 million workers, close to the number reported by BLS for that same period using a

different survey.¹⁴ This report primarily used ACS data from 2010 through 2016—specifically, we relied on the Census Bureau’s Public Use Microdata Sample of the ACS for the single years 2010, 2011, 2012, 2013, 2014, 2015, and 2016.

Analyses of Employment Trend Correlations

To test whether industries with higher concentrations of individuals in occupations susceptible to automation (as identified by Frey and Osborne) have experienced employment changes, we examined their correlation with changes in tech job concentration and changes in overall employment from 2010 through 2016. We limited the analysis to this period both because the ACS occupation codes changed in 2010 and because it allowed our results to post-date the economic recession of 2007-2009.¹⁵ We used industry definitions set by the ACS data, which groups some industries together—e.g., residential and nonresidential construction industries are combined in a single construction industry grouping. We defined tech jobs as those in computing, engineering, and mathematics occupations, consistent with previous GAO work on the tech field.¹⁶ We also examined an alternative definition of tech jobs in which we included those with “computer” in the occupation title. For both definitions, we estimated the number of tech jobs in each industry in each year, 2010-2016. We then calculated the growth rate in the number of tech jobs in each industry, and correlated that growth rate with the percentage of workers in that industry in occupations susceptible to automation (as identified by Frey and Osborne). We also estimated the number of workers overall in each industry in each year (2010-2016) and correlated the trend in total employment with the percentage of workers in that industry in occupations susceptible to automation (as identified by Frey and Osborne). We restricted our correlation analyses to those

¹⁴ For all analyses of ACS data, to account for the sample representation and design used in the ACS, we used the person weight present in the ACS data. We used the successive difference replication method to estimate the confidence interval around any population estimate. Using the Current Population Survey, BLS reported 25.2 million part-time wage and salary workers and 111.3 million full-time wage and salary workers; thus, totaling approximately 137 million workers in the fourth quarter of 2016.

¹⁵ According to the National Bureau of Economic Research, the 2007-2009 recession began in December 2007 and ended in June 2009.

¹⁶ See [GAO-18-69](#).

industries where the tech job growth rate or the overall employment trend was statistically significant.¹⁷

We performed two correlation tests. The Spearman test measures correlation between the rank of the two sets of values. The Pearson test measures correlation between the values themselves. As shown in table 2, we found a positive but weak correlation between industries with higher concentrations of jobs susceptible to automation and their concentration of tech jobs, based on both correlation tests and both definitions of tech jobs, and we found no meaningful correlation with change in overall employment in either test.

Table 2: Correlation Between an Industry’s Concentration of Jobs Susceptible to Automation and Growth in Tech Jobs or Changes in Overall Employment in That Industry, 2010-2016

Association between an industry’s percentage of jobs in occupations susceptible to automation and:	Growth in tech jobs (computing, engineering, and mathematics occupations)	Growth in tech jobs (occupations with “computer” in the title)	Change in overall employment
Spearman correlation coefficient	0.23	0.28	0.03
Pearson correlation coefficient	0.30	0.29	-0.01
Observations	69	57	125

Source: GAO analysis of data from the American Community Survey, 2010-2016. | GAO-19-257

Notes: The correlation coefficients measure the association between an industry’s percentage of jobs in occupations susceptible to automation and growth in tech jobs or changes in overall employment, 2010-2016. Growth in tech jobs and changes in overall employment are measured by the natural log of the population change. A positive coefficient implies that the variables tend to increase (or decrease) together. A negative coefficient implies an inverse relationship—e.g., as one variable increases, the other decreases. Values of the coefficient may range from -1.0 to +1.0. We restricted the correlation analyses to those industries where the tech job growth rate or the overall employment trend was statistically significant. We defined tech jobs in two ways: (1) jobs in occupations in the fields of computing, engineering, and mathematics, consistent with our previous work on the tech field, and (2) jobs with “computer” in the title of their occupation. For our previous work on the tech field, see GAO, Diversity in the Technology Sector: Federal Agencies Could Improve Oversight of Equal Employment Opportunity Requirements, [GAO-18-69](#) (Washington, D.C.: November 16, 2017). Occupations susceptible to automation are those that researchers Frey and Osborne estimated as having a probability of automation greater than 0.7—see Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016).

¹⁷ A correlation coefficient measures the association between two variables. A positive coefficient implies that the variables tend to increase (or decrease) together. A negative coefficient implies an inverse relationship—e.g., as one variable increases, the other decreases. Values of the coefficient may range from -1.0 to +1.0.

To explore an example industry—the plastics product manufacturing industry—in further detail, we identified the number of jobs susceptible to automation within that industry, by occupation and groups of occupations. We also examined the growth in tech jobs within the industry, by tech occupation. We approximated each occupation’s contribution to the overall growth of tech jobs in the industry by multiplying their individual growth rates over the period 2010-2016 by their employment in 2010. The growth rates for the three engineering occupations, which when combined, account for more than half of the industry’s growth in tech jobs, were each significant at the 85 percent confidence level.

Analyses of Worker Characteristics and Earnings

To analyze the characteristics of workers in occupations susceptible to automation (as identified by Frey and Osborne), as well as the characteristics of workers with tech jobs, we used 2016 ACS data. We examined data on the workers’ gender, level of education, age, race and ethnicity, and hourly wage, and compared distributions of workers in occupations susceptible to automation and workers in all other occupations (see table 3). For race and ethnicity categories, we included only non-Hispanic members of White, Black, Asian, and Other categories, and the Hispanic category included Hispanics of all races. The “Other” category included American Indian or Alaskan Native, Native Hawaiian or Pacific Islander, two or more races, and other race. To analyze education level, we combined all attainment levels from a high school degree or less. To estimate the hourly wage of workers, we divided the wage and salary earnings of the worker by their usual hours worked and weeks worked. To test the reliability of this measure, we compared our results to average hourly wages reported by other BLS surveys; we found that the average values were sufficiently close to determine that this method was sufficiently reliable for our purposes.

Table 3: Characteristics of Workers in Jobs Susceptible to Automation and Tech Jobs, 2016

Worker population:	Workers in jobs susceptible to automation	Workers in jobs not susceptible to automation	Workers in tech jobs	Workers in non-tech jobs
Number of workers	58.7 million	77.7 million	7.2 million	129.2 million
Median age	39 years	41 years	41 years	40 years
Mean hourly wage	\$17.37	\$26.94	\$39.68	\$21.88
Median hourly wage	\$14.26	\$22.06	\$36.76	\$17.16
Percent of workers in the below groups who hold jobs of the specified type:				
Total workers	43.0 percent	57.0 percent	5.3 percent	94.7 percent
Male	44.1 percent	55.9 percent	8.1 percent	91.9 percent
Female	41.9 percent	58.1 percent	2.4 percent	97.6 percent
Asian, non-Hispanic	35.9 percent	64.1 percent	15.9 percent	84.1 percent
Black, non-Hispanic	46.4 percent	53.6 percent	3.0 percent	97.0 percent
Hispanic	54.1 percent	45.9 percent	2.3 percent	97.7 percent
White, non-Hispanic	40.0 percent	60.0 percent	5.6 percent	94.4 percent
Other, non-Hispanic	45.2 percent	54.8 percent	4.9 percent	95.1 percent
Graduate degree	11.3 percent	88.7 percent	10.6 percent	89.4 percent
Bachelor’s degree (BA)	26.9 percent	73.1 percent	11.3 percent	88.7 percent
Some college, but less than a BA	46.7 percent	53.3 percent	3.9 percent	96.1 percent
High school degree or less	60.7 percent	39.3 percent	1.0 percent	99.0 percent

Source: GAO analysis of data from the American Community Survey, 2016. | GAO-19-257

Notes: Group row percentages that differ from the row percentage for total workers represent disproportionate representation (over- or under-) of a group in a specific job type. For example, workers with a high school degree or less disproportionately hold jobs susceptible to automation, and Asian, non-Hispanic disproportionately hold tech jobs. Row percentages shown may not sum to 100 percent due to rounding. All percentage estimates shown have margins of error that are within +/- 0.65 percentage points or less, at the 95 percent confidence level. All other estimates have 95 percent confidence intervals with margins of error that are within +/- 1.72 percent of the estimates themselves. Jobs susceptible to automation are those in occupations that researchers Frey and Osborne estimated as having a probability of automation greater than 0.7—see Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016). Tech jobs are those in occupations in the fields of computing, engineering, and mathematics, consistent with previous GAO work on the tech field—see GAO, *Diversity in the Technology Sector: Federal Agencies Could Improve Oversight of Equal Employment Opportunity Requirements*, [GAO-18-69](#) (Washington, D.C.: November 16, 2017).

To investigate whether differences in hourly wage might be due to other factors, we estimated multiple regression models that enabled us to control for additional variables. Specifically, we estimated wage differences between workers in occupations susceptible to automation and workers in other occupations—i.e., whether a worker was in an occupation susceptible to automation (as identified by Frey and Osborne)

was our primary independent variable (a binary, yes/no variable). Because we used the natural log of the hourly wage as the dependent variable, the standard interpretation of the regression coefficient of this variable is that it represents the average log point difference in hourly wages between occupations susceptible to automation and all other occupations. This coefficient can be made to more closely approximate a percentage difference in hourly wages or an earnings gap by taking the exponent and subtracting 1. As noted previously, we limited our analysis to workers who earned positive wage and salary income in the prior 12 months. We also removed observations with outlier values for wages (e.g., wage rates above \$140 per hour); this represented about 1 percent of the sample in 2016.

We ran five regression models with different sets of independent variable controls.

- Regression (1) estimates the earnings gap without any controls (the uncorrected earnings gap).
- Regression (2) estimates the earnings gap with a set of independent variables that control for characteristics of the individual; these variables included age, race and ethnicity, gender, marital status, state of residence, and education level.
- Regression (3) estimates the earnings gap with independent dummy variables for 2-digit industry codes added; this corrects for any differences between industries at the 2-digit level.
- Regression (4) estimates the earnings gap with independent dummy variables for 2-digit occupation codes added; this corrects for any differences between occupations at the 2-digit level.
- Regression (5) includes both 2-digit industry and 2-digit occupation code dummy variables.

As table 4 shows, we found a significant difference in hourly wages between workers in occupations susceptible to automation compared to workers in other occupations, even after independent variables to control for worker characteristics, industry, and occupation codes were included. Including the additional independent variables caused the earnings gap to fall from just over -34 percent to just over -10 percent. Regression model 3, which estimated an earnings gap of about -17.2 percent, is our preferred model, as it controls for individual worker characteristics and for any differences between industries at the 2-digit level, but does not include occupation as an independent variable. Including occupation

variables controls for any differences between occupations at the 2-digit level. However, because we identify workers in jobs susceptible to automation based on their occupations, these occupation control variables are likely highly predictive of Frey and Osborne’s estimated probability of automation, which is used to categorize workers in jobs susceptible to automation. We also ran these regression models for other years from 2010 to 2016 and we found substantively similar results.

Table 4: Estimated Hourly Wage Differences Between Workers in Occupations Susceptible to Automation and Workers in Other Occupations

Regression model:	(1)	(2)	(3)	(4)	(5)
Regression coefficient on dummy variable for workers being in an occupation susceptible to automation (with T-statistic)	-.42 (-336)	-.177 (-157)	-.188 (-166)	-.11 (-80)	-.11 (-84)
Regression coefficient presented as the percent difference in the hourly wage of workers in occupations susceptible to automation compared to all other workers	-34.3 %	-16.2 %	-17.2 %	-10.3 %	-10.6 %
Worker characteristics included as independent variables?	No	Yes	Yes	Yes	Yes
2-digit industry codes included as independent variables?	No	No	Yes	No	Yes
2-digit occupation codes included as independent variables?	No	No	No	Yes	Yes
R2	.08	.35	.39	.41	.42
Observations	1.3 million	1.3 million	1.3 million	1.3 million	1.3 million

Source: GAO analysis of data from the American Community Survey, 2016. | GAO-19-257

Notes: All regression coefficients are statistically significant at least at the level of p-value < 0.05. T-statistics are presented in parentheses below the regression coefficients. Because we used the natural log of the hourly wage as the dependent variable, the regression coefficients represent the average log point difference in hourly wages between occupations susceptible to automation and all other occupations. In the next row of the table, this coefficient is converted to more closely approximate a percentage difference in hourly wages by taking the exponent of the coefficient and subtracting 1. Various independent variables capture and control for many different characteristics across workers, yet unobservable factors that may cause earnings differences may exist; thus, regression results do not prove causality. Worker characteristics that we controlled for included age, race and ethnicity, gender, marital status, state of residence, and education level. Occupations susceptible to automation are those that researchers Frey and Osborne estimated as having a probability of automation greater than 0.7—see Carl Frey and Michael Osborne, “The Future of Employment: How Susceptible Are Jobs to Computerisation?,” *Technological Forecasting & Social Change* (2016).

Section 2: Analyses Using Data from the Current Population Survey’s Displaced Worker Supplement

This section discusses the quantitative analysis methods we used to compare relative job displacement rates between workers in occupations susceptible to automation (as identified by Frey and Osborne; see above) and workers in other occupations. We used data from the CPS’s Displaced Worker Supplement for these analyses.

The CPS is sponsored jointly by Census and BLS and is the source of official government statistics on employment and unemployment in the United States. The basic monthly survey is used to collect information on employment, such as employment status, occupation, and industry, as well as demographic information, among other things. The survey is based on a sample of the civilian, non-institutionalized population of the United States. Using a multistage stratified sample design, about 56,000 households are interviewed monthly based on area of residence to represent the country as a whole and individual states; the total sample also includes additional households, some of which are not interviewed in a given month for various reasons, such as not being reachable. The CPS Displaced Worker Supplement has been administered every other year since 1984, and provides supplemental data on persons age 20 years or older who lost a job involuntarily in the prior 3 years, including data on reasons for job displacement, as well as industry and occupation of the former job. This report used data from the January 2016 Displaced Worker Supplement.

Analyses of Relative Job Displacement Rates

To analyze whether workers in occupations susceptible to automation (as identified by Frey and Osborne) experience job displacement at differing rates than workers in other occupations, we used data from the CPS's January 2016 Displaced Worker Supplement. We identified workers who lost or left a job involuntarily during the 3 calendar years prior to the survey (i.e., January 2013 through December 2015) because their position or shift was abolished or because there was insufficient work for them to do. We focused on these reasons for displacement as those that most closely approximate how advanced technologies could replace workers at a given firm.¹⁸ We also limited our analysis to those workers who did not expect to be recalled to their jobs within the next 6 months. We categorized these displaced workers according to the occupations from which they were displaced (e.g., workers displaced from occupations susceptible to automation and workers displaced from all other occupations).

We calculated relative job displacement rates as the number of displacements over the period 2013-2015 reported by a given population (e.g., workers in occupations susceptible to automation), over that

¹⁸ Potential reasons for displacement identified in the survey include the plant or company closed down or moved; insufficient work; position or shift abolished; seasonal job completed; self-operated business failed; some other reason; and the respondent did not know or refused to provide a response.

population's total current employment in January 2016. Although this measure does not represent the total number of jobs that existed annually that could have resulted in displacements, it allows us to control for population size and to approximate a relative displacement rate. We examined various populations, including occupations identified as susceptible to automation by Frey and Osborne, occupations BLS projects will experience declines in their share of employment due to advanced technologies (see above), and production occupations. To categorize occupations, Frey and Osborne and BLS use Standard Occupational Classification (SOC) codes, whereas the Displaced Worker Supplement uses Census occupation codes. We used a crosswalk provided by Census to match these occupation classifications. SOC codes have a hierarchical structure—e.g., a “broad” occupation group contains a subset of “detailed” occupations. For example, SOC code 13-1031 is the detailed occupation “claims adjusters, examiners, and investigators” within the broad group SOC 13-1030 (“claims adjusters, appraisers, examiners, and investigators”). When a direct crosswalk between SOC and Census occupation codes was not available at the detailed level, we used the associated broad SOC group to identify a Census occupation code. There were some respondents in the Displaced Worker Supplement who did not report the occupation from which they were displaced, and these were dropped from our analysis.

To estimate the sampling errors for each estimate, we used strata defined by state because the Displaced Worker Supplement data did not provide replicate weights or the sampling strata necessary to obtain standard errors. When estimating the number of job displacements over the period 2013-2015 reported by a given population (e.g., workers in occupations susceptible to automation), we used the supplement weight for respondents. When estimating the population's total current employment in January 2016, we used the CPS 2016 weight for respondents. We used a Taylor series linearization to estimate the sampling error of the ratio of estimated number of job displacements over the period 2013-2015 to the estimated number of current employment in 2016.

While our primary analysis examined relative displacement rates for workers in occupations susceptible to automation, we also conducted sensitivity analyses by considering other groups of occupations. Specifically, we examined the relative displacement rates of the following groups:

-
- Jobs susceptible to automation had a relative displacement rate of 3.4 percent +/- 0.3, and all other jobs combined had a relative displacement rate of 2.9 percent, +/- 0.2.
 - Jobs in occupations BLS projects will experience relative declines in employment due to advanced technologies (see above) had a relative displacement rate of 3.7 percent, +/- 0.5, and all other jobs combined had a relative displacement rate of 3.6 percent, +/- 0.2.
 - Jobs in production occupations had a relative displacement rate of 3.7 percent +/- 0.8, and all other jobs combined had a relative displacement rate of 3.1 percent, +/- 0.2.

Section 3: Analyses Using Data from the Occupational Employment Statistics survey

This section discusses the quantitative analysis methods we used to analyze geographic reliance on occupations susceptible to automation (as identified by Frey and Osborne; see above). We used OES data for these analyses.

The OES survey is a federal-state cooperative effort between BLS and state workforce agencies, which collects information on occupational employment and wage rates for wage and salary workers in nonfarm establishments. The survey is based on a sample drawn from about 7.6 million in-scope nonfarm establishments in the United States that file unemployment insurance reports to the state workforce agencies. Using a stratified sample design, about 200,000 establishments are surveyed semiannually and employment estimates are based on six panels of data collected over a 3-year cycle. The final in-scope sample size when six panels are combined is approximately 1.2 million establishments. The OES survey includes all full- and part-time wage and salary workers in nonfarm industries, but excludes self-employed workers, owners and partners in unincorporated firms, household workers, and unpaid family workers. OES data provide occupational employment estimates by industry for the country as a whole, for individual states, and for more local geographic areas (e.g., metropolitan and nonmetropolitan areas). This report used data from the May 2017 Occupational Employment Statistics.

Analyses of Geographic Reliance on Occupations Susceptible to Automation

To analyze what U.S. geographic areas rely more heavily on employment in occupations susceptible to automation, we used data from the May 2017 OES. For each local geographic area, we estimated how many jobs were in occupations identified as susceptible to automation by Frey and

Osborne (see above) and how many jobs were in all other occupations.¹⁹ We also estimated how many jobs were in each group of occupations nationwide (using national-level data). We then calculated a location quotient for each local geographic area, which measures the proportion of each area's jobs that were in occupations susceptible to automation compared to the national proportion of employment in these occupations. This measure depicts the extent to which a local geographic area relies on certain jobs for the employment of its population, relative to other areas.²⁰

Based on their location quotients, we categorized and mapped 589 local geographic areas in the following three groups:

- **Relatively High Concentration:** Areas where the proportion of jobs susceptible to automation is at least 5 percentage points greater than the national average, and the difference is statistically significant at the 95 percent confidence level. This translates to an estimated location quotient of at least 1.1.²¹
- **Average or Relatively Low Concentration:** Areas where the proportion of jobs susceptible to automation is within 5 percentage points above the national average or lower.
- **Undetermined Reliance:** Areas where the proportion of jobs susceptible to automation is undetermined. We classify an area's proportion as "undetermined" if the estimated margin of error at the 95 percent confidence level is larger than 5 percentage points.

We conducted one sided z-tests at the 95 percent confidence level to analyze each area's estimated location quotient. The null hypothesis is

¹⁹ We use the term "local geographic area" to describe the geographies we analyzed. These consist of metropolitan statistical areas and nonmetropolitan areas (which appear in the OES data as "balance of state" areas).

²⁰ According to BLS, a location quotient is a ratio that, in this context, compares the concentration of occupational employment in a defined area to the national average concentration. Location quotients greater (or less) than one indicate employment in the occupation(s) is more (or less) prevalent in the area than in the United States as a whole.

²¹ The estimated national share of employment in these occupations is approximately 45 percent of total employment; thus, areas with estimated shares of employment in these occupations that are 5 percentage points greater than the national average (i.e., 50 percent) have a location quotient of 1.1 (i.e. $0.5/0.45 = 1.1$). This estimated employment share threshold (i.e., 50 percent) aligned with the top 25 percent of all 589 local geographic areas, disregarding sampling variability and statistical significance.

that the area location quotient is less than or equal to 1.1 (i.e., the proportion of employment in the group of occupations in an area is 1.1 times the national proportion). The alternative hypothesis is that the area location quotient is greater than 1.1. Because estimated area employment proportions are based on a sample, we also restricted our tests to those areas that were reliable for our purposes by requiring that areas had sampling errors of no greater than 5 percentage points for a 95 percent confidence interval.

According to BLS, employment estimates for individual occupations in individual local geographic areas may not be available in the public data for a variety of reasons, including for example, failure to meet BLS quality standards or to ensure the confidentiality of survey respondents. Because we aggregate data across multiple occupations, our methodology treats these cases as if employment in the given occupation in the given area was zero, which is not the case and which introduces imprecision into our analysis and the resulting location quotients. However, because ensuring confidentiality is a primary concern, we assume that most of these cases where data are suppressed would have relatively small numbers of jobs, and thus have minimal effects on our results. To test this assumption and to ensure the appropriateness of our methods, we compared the total number of jobs we analyzed across all local geographic areas to the total number of jobs reported at the national level (which do not have data suppressed). The total number of jobs analyzed across our local geographic areas was 5.5 percent lower than the total number of jobs reported at the national level, which we concluded was within an acceptable threshold to determine that the data were sufficiently reliable for our purposes and our analysis.²² In addition, according to BLS, because occupational employment estimates are rounded to the nearest 10 before publication, estimates of location quotients calculated from the public data will be subject to some rounding error, compared with location quotients calculated from the unrounded pre-publication data.

²² The total number of jobs in occupations susceptible to automation across our local geographic areas was 4.5 percent lower than the total reported at the national level. The total number of jobs in all other occupations across our local geographic areas was 6.3 percent lower than the total reported at the national level.

Appendix II: Comments from the Department of Labor

U.S. Department of Labor

Office of the Assistant
Secretary for Policy
Washington, D.C. 20210



February 12, 2019

Ms. Cindy S. Brown Barnes,
Director
Education, Workforce, and Income Security Issues
U.S. Government Accountability Office
441 G Street, N.W.
Washington, D.C. 20548

Dear Ms. Barnes:

Thank you for the opportunity to review and comment on the Government Accountability Office's (GAO) draft report titled, *Workforce Automation: Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs* (GAO-19-257, job code 102395). The Department of Labor (Department) appreciates GAO's work to provide information regarding the potential impacts related to the adoption of advanced technologies, including but not limited to artificial intelligence (AI), as well as the progress and challenges for Federal agencies to track the potential impact of advanced technologies. The Department is committed to understanding the potential impact of advanced technologies on the workforce; developing new, relevant and comprehensive measures on the nature of employment; and aligning workforce development programs to continue to meet the needs of employers and workers.

The Department agrees with GAO's recommendation and will continue to explore how we might develop ways to use existing or new data collection efforts to identify and track the workforce effects of advanced technologies. The Department has already begun exploring the potential impact of advanced technologies and is coordinating with the Census Bureau on research activities in this area. Specifically, the Department plans to examine the interaction between labor and capital in the workplace and how this is affected by new technologies, such as automation, digitization, and AI; identify how the key constructs are currently captured by domestic and international statistical agencies; and recommend data collection options to fill those gaps as well as methodologies for leveraging existing data.

In addition, the Department will continue to inform the public about projected structural changes in the mix of occupations and industries through its Employment Projections. The projections are the foundation of the Occupational Outlook Handbook, one of the nation's most widely used career information resources. In order to provide more timely information to the public, the Department will be releasing new Employment Projections annually, rather than every two years, beginning in 2019.

The Department will continue to provide information to the general public through the O*NET database and supporting websites, which offer a variety of search options and

occupational characteristics and requirements data. The O*NET system is based on a database that includes information on skills, abilities, knowledge, work activities, and interests associated with occupations. This information is available for over 900 occupations, and can be used to facilitate career exploration, vocational counseling, and a variety of human resources functions, such as developing job orders and position descriptions and aligning training with current workplace needs.

Thank you for the opportunity to respond.

Sincerely,



Stephanie Swirsky
Deputy Assistant Secretary

Appendix III: GAO Contact and Staff Acknowledgments

GAO Contact

Cindy Brown Barnes, (202) 512-7215, brownbarnesc@gao.gov

Staff Acknowledgments

In addition to the contact named above, Blake Ainsworth (Assistant Director), Michael Kniss (Analyst-in-Charge), Shilpa Grover, and John Lack made key contributions to this report. Also contributing to this report were James Bennett, Benjamin Bolitzer, Melinda Cordero, Holly Dye, Jonathan Felbinger, Sheila R. McCoy, Jean McSween, James Rebbe, Krishana Routt-Jackson, Benjamin Sinoff, Almeta Spencer, and Sonya Vartivarian.

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