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OXFORD ECONOMICS

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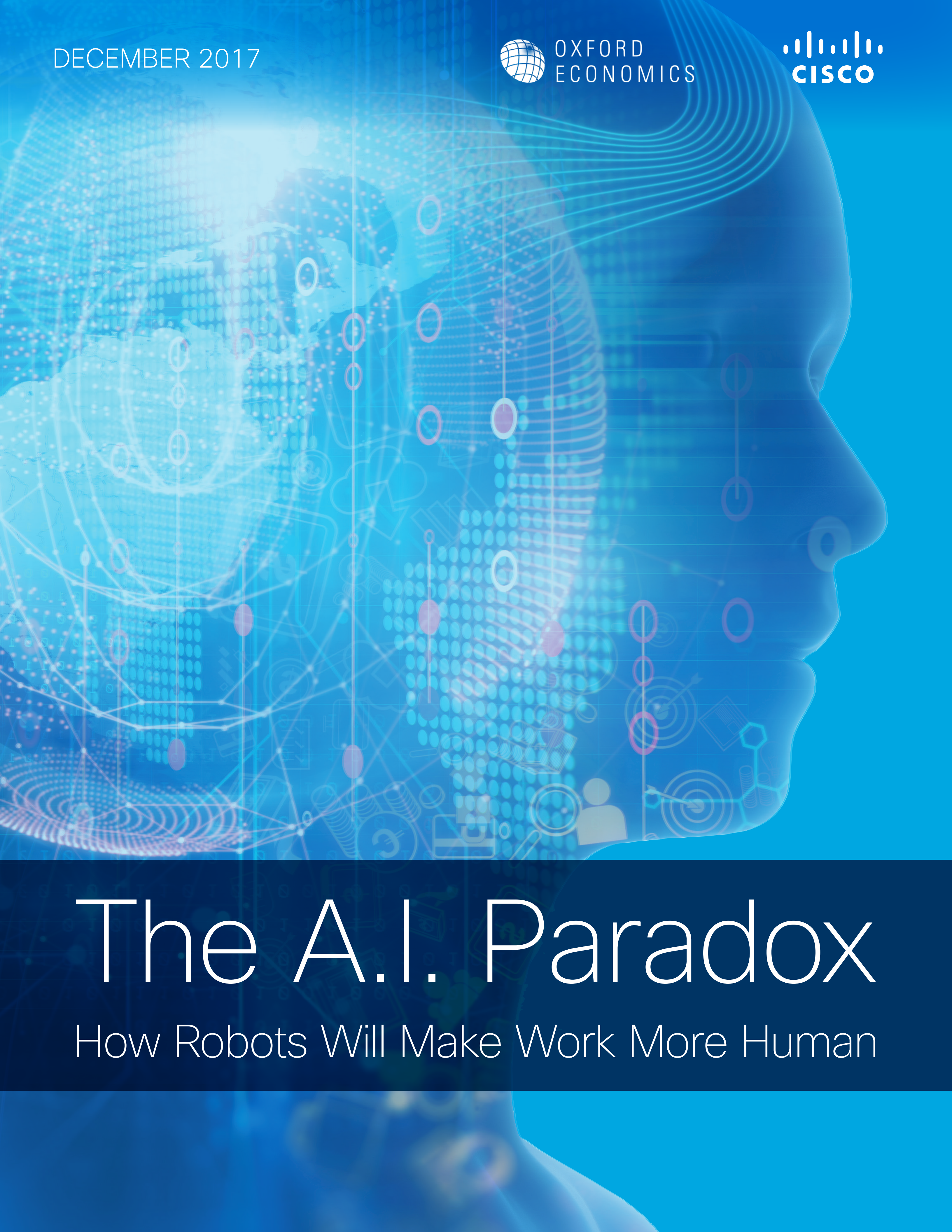

The A.I. Paradox

How Robots Will Make Work More Human

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Foreword

We live in a world where technological innovation is a constant. The recent pace of technological advancement is unprecedented. For instance, by 2030, it is expected that there will be 500 billion devices and objects connected to the Internet. The impact of automation, artificial intelligence, and the Internet of Things (IoT) is being felt almost everywhere, in all industries, jobs and everyday life. Given this pace of change, it is important to understand and anticipate what this means for future jobs, youth, and society more broadly, so that everyone has an opportunity to participate in the digital economy.

At Cisco, we want to help answer these questions through research and contribute to the continuing dialogue on technology's future impact. We believe Cisco has a role to play. We hope to serve as a catalyst for driving an inclusive digital economy. To do so, we conduct research to gain a better understanding of future skill needs, anticipate where jobs will be, and help shape the role of technology to build the workforce of today and tomorrow. These insights enable us to make investments that not only help meet industry demand for a digitally skilled workforce, but also help shape entirely new ideas and industries to fuel the digital economy and create the jobs of the future. We use these insights to ensure the relevance of key corporate social responsibility (CSR) investments. For example, our Cisco Networking Academy program reaches over a million students worldwide and provides individuals with foundational digital and entrepreneurial skills that improve their career prospects while helping fill global demand for technology professionals.

To uncover key insights and build our understanding, we worked with Oxford Economics, who brings a wealth of knowledge and expertise. We worked with them to develop a model that estimates how both displacement and job creation will be spread across the economy. We also wanted to understand which work activities, occupations, and industries will be affected along with how individuals can move around the labor market. The results highlight the need for technology skills across jobs and industries as most jobs in the future are technology jobs. In addition to technology skills, the model highlighted that it is the human skills that will be most in demand, including negotiation, persuasion, service orientation, instructing, social perceptiveness and coordination.

To help take advantage of the opportunities technology can bring, we at Cisco are working toward empowering global problem solvers who embody both the technology and human skills needed to be successful. We believe that global problem solvers—individuals that innovate as technologists, think as entrepreneurs, and act as social change agents—will be key to fueling an inclusive digital economy. Using this research, we can better design our programs and investments to develop and support global problems solvers who apply digital solutions to address social problems and foster economic development. We have a bold goal to positively impact 1 billion people by 2025.

Though we do not fully know what the future holds, if we empower people to become global problem solvers and prepare them with the right skills, we can help them participate in the global economy and create economic opportunity for all.

Executive Summary

We are living in an era of revolutionary technological change that is transforming the world of work. Each day around 150 million Americans make their way to work, providing for themselves and their families, and driving the U.S. economy forward. But what will happen to these millions of jobs as technology reshapes the labor market over the coming decade? The question of technology's impact on the number and nature of jobs in the future has been the subject of pronounced interest to academics, technology experts, and futurists. Headline-grabbing findings have been widely reported in newsrooms, eliciting fears that technology threatens to alter profoundly our relationship with work.

The popular narrative is that automation and artificial intelligence will lead to largescale unemployment as robots replace jobs. In 2013, a prominent study by Carl Benedikt Frey and Michael Osborne at the University of Oxford caught the public's imagination. Their study predicted that almost half the working population of the United States would be vulnerable to automation in the next two decades.[1] They were not alone in positing such an uncomfortable view of the future. Eric Brynjolfsson and Andrew McAfee, from the Massachusetts Institute of Technology, described a future in which large sections of the labor force faced chronic underemployment,[2] while futurist Martin Ford warned of technology gradually squeezing workers out of the production process.[3]

However, technological change leads to job creation as well as automation, and these two effects are interdependent: History has repeatedly borne this out. Technological innovations are leveraged by businesses to improve their productivity. This alters the demands on their workforce, often displacing some workers from their jobs. Such change, however, also leads to a growth in prosperity, generating additional demand, which, in turn, creates new and different jobs. Employment in agriculture is a famous example. In the year 1900, roughly half of all U.S. workers were employed on farms. Today, that ratio stands at less than two percent. This reshaping of the labor market occurred thanks to mechanization—the technological transformation of the day—which enabled the sector to produce much more food with far fewer workers. Certainly farm-hands lost their jobs, which would have affected their livelihoods in the short-term. But as cheaper agricultural prices redistributed consumer spending, those workers were employed elsewhere. From an aggregate perspective, millions of surplus farm-hands left agriculture and moved into new jobs, which were typically better paid.

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1 Frey, C. B. & Osborne, M. A. (2013) "The Future of Employment: How Susceptible are Jobs to Computerisation?" Mimeo. Oxford Martin School.
2 Brynjolfsson, E, & Andrew M. (2014) "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies." New York.
3 Ford, M. (2015) "The Rise of the Robots" Basic Books, New York.

Which jobs will be automated and what will those employees do?

Where in the economy will new jobs emerge and who will fill them?

What skills shortfalls will the workforce need to bridge in order to smooth the transition from the old economy to the new?

Technology primarily causes a change in the nature of work, rather than the number of jobs. Even with the giant technological leaps forward of the last century, right up to the digital revolution of the last decade, the U.S. has never experienced lasting "technological unemployment"—a term popularized by John Maynard Keynes in the 1930s. In fact, employment levels today are at their highest point in history. It is, however, important to recognize that there are social consequences attached to the evolution of the labor market, even if employment rates remain buoyant. The transition into new jobs can often be very challenging for workers, and the changing shape of the labor market has raised concerns about a stratification in society between the rich and the poor. In particular, as technology becomes increasingly good at automating more cognitive tasks, some economists point to a "hollowing-out" of the labor market as workers in routine, mid-skilled jobs are disproportionately hit and jobs spread out to the lower- and higher-skilled ends of the jobs market. Preparing for these complex dynamics, and the skills challenges they imply, requires a nuanced understanding among policymakers, business leaders and educators of how technological change will affect the nature of people's jobs.

This study uses unique modeling techniques to explore how the labor market will evolve, shedding light on the challenges ahead in a more comprehensive way than ever before. This study also goes beyond existing efforts to identify the jobs at risk of automation to forecast where new jobs will be created. In doing so, it answers vital questions: Which jobs will be automated and what will those employees do? Where in the economy will new jobs emerge and who will fill them? And what skills shortfalls will the workforce need to bridge, in order to smooth the transition from the old economy to the new?

To understand how the labor market will change, we have explored what the U.S. economy will look like in 10 years. We worked with a group of Cisco technology experts to build a vision of the technology landscape in 2027. It describes a world in which companies use detailed customer data to provide heavily personalized and tailored services; where networked robots provide flawless manufacturing quality in the supply chain; and where, in offices across the country, artificial intelligence not only out-performs people in routine tasks, but also increasingly makes more complex decisions for us.

Beyond this qualitative vision of the future, we provide a quantitative assessment of what technological change means for the world of work. We mapped expert findings to detailed occupational and labor market datasets to develop a comprehensive profile of how technology advancements will affect productivity. This revealed which jobs are likely to be most exposed to competition from new technologies over the next decade. But as we have seen, the threat of automation is only part of the story. Our model enables us to go much further. It provides an assessment of the opportunities presented to today's workforce, as technology cuts the cost of production, lowering prices and leaving consumers with more money to spend. It examines what, until now, nobody has explored: how technology will change the labor market—by displacing but also creating jobs—and the transition today's workers will have to make to be ready for the future.

4.3 million
U.S. workers will be displaced by new technologies by 2027

6.5 million
U.S. workers will move jobs as a result, to adapt to the new landscape

Our model predicts a transformation of the labor market in which around 6.5 million workers will need to find a new form of employment, as a wave of technological change washes through the U.S. economy. Despite the innovations heralded by our technology scenario, there is no reason to believe this will lead to large-scale unemployment. However, there will still be significant upheaval. In our scenario, around 4.3 million workers are displaced from their jobs by technological innovation. But as workers move, the vacancies cascade throughout the labor market, and the displacement of 4.3 million workers leads to almost 6.5 million total job moves before the future labor market returns to equilibrium. This is over and above the everyday "churn" that normally occurs in the labor market, and it is equivalent to 4.9 percent of the current working population.

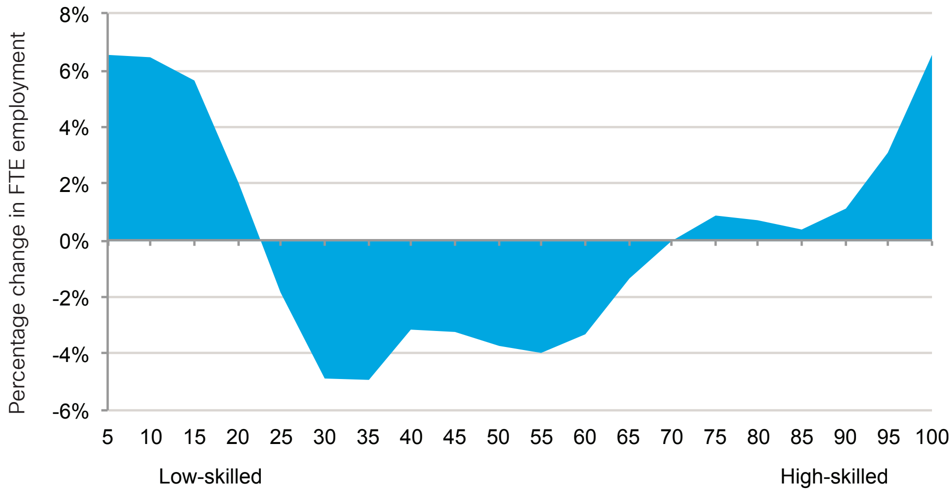
For many people, the nature of the work they do will change considerably: Technology will increasingly take on the most repetitive and regimented tasks, freeing people up to work on the things that people do best. We have been able to model the implications of widespread technological change over the coming decade by breaking down what the workforce does into discrete tasks. The people whose jobs are most vulnerable to disruption, as in the past, will continue to be those who do routine and repetitive tasks whether cognitive (such as documenting information) or physical (such as moving objects). But vacancies elsewhere in the economy will mean surplus workers are pulled into new opportunities.

Our results show that the "hollowing out" phenomenon is likely to continue. Fig. 1 presents a high-level picture of how we project technological change to affect different segments of the workforce over the next decade. Broadly, we anticipate growth in jobs at the lower-skilled end of the labor market; namely those that are less easily automatable such as dish-washers and personal care aides. There is also an increase in jobs at the higher-skilled end of the market, such as commercial pilots and electrical engineers, as well as Information Communications Technology (ICT) professionals. As in the past two decades, this is accompanied by a decline in the share of the middle of the skills spectrum—a large category including occupations like legal secretaries and truck drivers. Underneath the broad trend portrayed in Fig. 1, of course, the impact is much more complex. Our detailed analysis shows how some workers at the top and bottom ends of today's skill-spectrum will likely be displaced by new technological innovations, while some workers in the mid-skilled range will find their contribution more highly valued when augmented by technology. The impact of technology depends on the specific characteristics of each role.

4% Increase in healthcare workers in 2027 economy

7% Increase in salespeople required in 2027 economy

Fig. 1 How technological change will affect workers in low, mid and high-skilled jobs Projected change in employment by percentile of the workforce (presented as five-percentile aggregates, ranked by 2015 mean wage as a proxy for skill level).



Source: Oxford Economics

This study reveals a detailed picture, not just of where the jobs will be in 2027, but of the moves people will make in the transition from today's workforce to the workforce of the future. It shows that workers in transport, lower-level manufacturing and agriculture can expect to be significantly affected over the next decade. At the same time, many new jobs will be created in computing, management and media, as well as in healthcare and sales. For instance, our projections suggest that four percent more healthcare workers will be required in 2027 and almost seven percent more salespeople–a category including online business development as well as in-person retail assistants.

Who will fill the new jobs created and where will the displaced workers go? A worker displaced from a security guard job, after all, is unlikely to fill a vacancy in web design. To understand worker movement, we developed a sophisticated skills-matching model to simulate how the labor market would respond to the technology scenario we defined. The model fills job openings iteratively by finding candidates that most closely match the skills and experience required in the role. Job openings are created directly by virtue of our technology scenario, as demand grows in certain areas of the economy. They are also created indirectly, as workers are attracted into new, potentially more lucrative positions and leave a vacancy in their wake. The model matches vacancies with candidates iteratively until all the openings are filled and the market returns to equilibrium.

The U.S. is facing a **crucial reskilling challenge.**

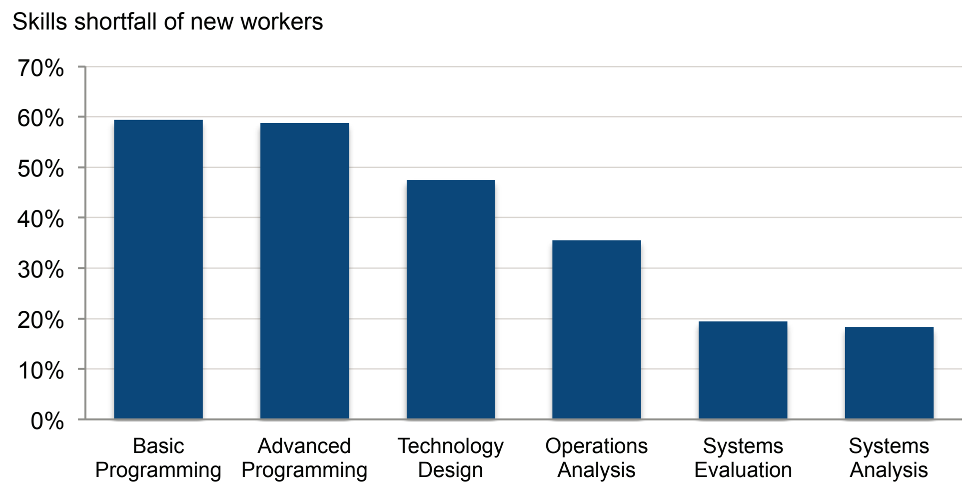
The economy's most acute skills shortage will be in Information and **Communications Technology (ICT)**

59% Shortfall in programming skills by 2027

The 6.5 million workers moving jobs in our scenario will face significant challenges in adapting to their new roles. By tracing the moves that workers make, our model enables us to measure the "skills shortfalls" they will have to bridge. We compared the detailed skills profiles of the original job and the new one, to analyze the implied training needs for every moving worker. Aggregating those impacts paints an unprecedented picture of the future skills shortfalls facing the U.S. labor market. Some of these skills will likely be picked up on the job, but others will not. This study gives policymakers, business leaders and educators insights into the areas they will need to focus on to address skills gaps in the future U.S. economy.

Our model shows that the U.S. is facing a crucial reskilling challenge, and that the economy's most acute skills shortage will be in Information and Communications Technology (ICT). Our analysis points to the major transitional bottlenecks in the labor market that must be addressed if the opportunities presented by technological innovation are to be realized. Fig. 2 reveals the shortfall in ICT skills, as defined by the O*NET database,[4] that today's workers face in meeting the demands of the 2027 economy. For all workers moving into new positions in our scenario, this chart shows what proportion of the ICT skills required are lacking. We found advanced and basic programming skills to top the training requirements, with new workers bringing only around 40 percent of the skills they need to their new jobs. This includes the steep learning curve implied by new, ICT specialist positions as well as the lower-level programming skills that will be required across a broad spread of industries in 2027, including the arts, healthcare and finance. The ICT skills shortfall goes beyond programming. We found significant gaps in a broader suite of ICT skills too, including technology design, operations analysis, systems evaluation and systems analysis.

Fig. 2 ICT skills shortfall (Proportion of required ICT skills that are lacking in workers moving into ICT-relevant jobs by 2027)



Source: Oxford Economics

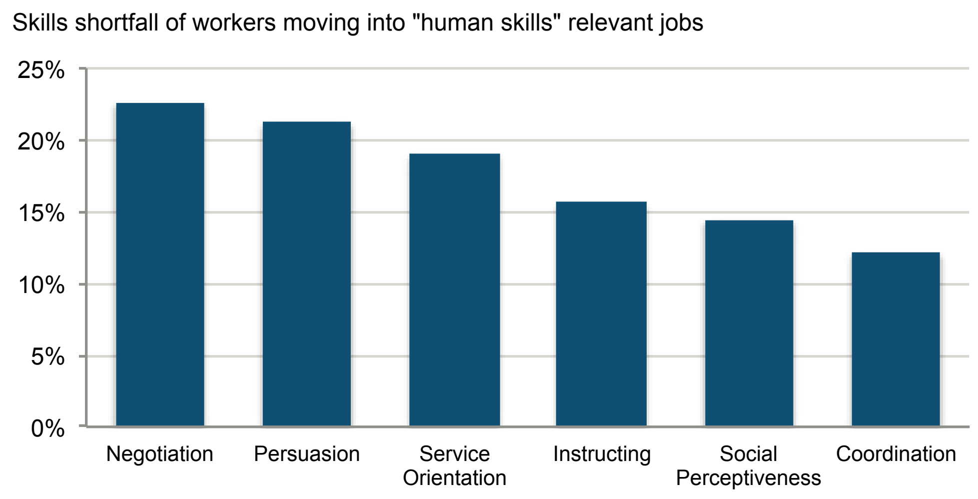
4 O*NET is an online database of occupational definitions and insights, sponsored by the U.S. Department of Labor. For more information on O*NET and how we used it, see Annex 4.

32% of the overall 2017 skills gap is in "human skills"

23% Shortfall in negotiation skills by 2027

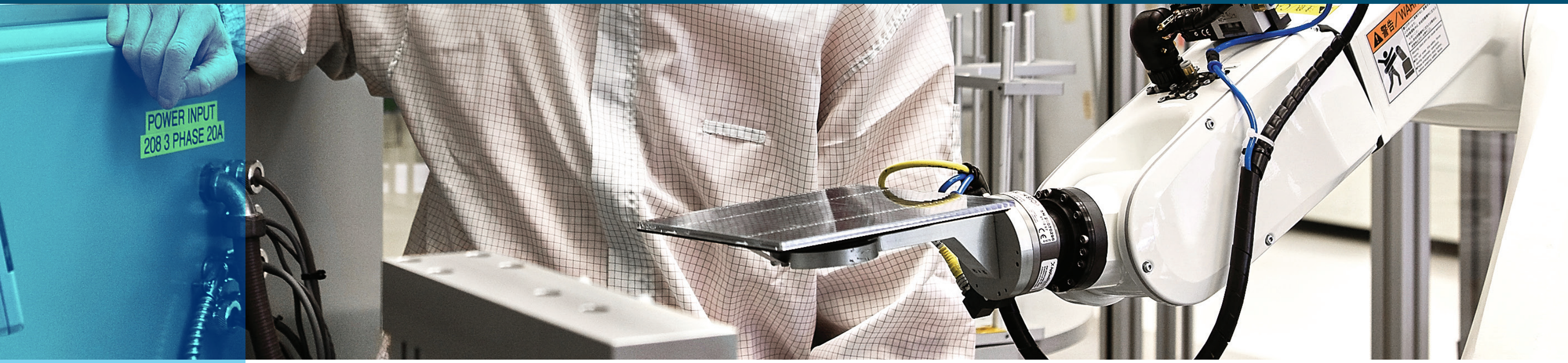
Paradoxically, as technology becomes more powerful and capable, there will be an accompanying rise in demand for "human skills" alongside digital ones. Our analysis found that 32 percent of the overall skills gap by 2027 will be in skills that are inherently "human," relating to interpersonal communication, perceptiveness and persuasiveness. Success in these areas will be defined by people's ability to out-perform technology, or to work creatively with technology, rather than compete against it. As technology grows more powerful over the next decade, job opportunities will abound for workers who can leverage these inherently "human" skills most effectively. As a result, the U.S. labor market faces a less obvious but very significant skills shortfall in such areas as negotiation, persuasion, service orientation, social perceptiveness and coordination, as displayed in Fig. 3.

Fig. 3 "Human" skills shortfall (Proportion of required "human" skills that are lacking in workers moving into relevant jobs by 2027)



Source: Oxford Economics

The intersection of ICT and "human" skillsets embodies the economy's ability to make the best use of technological innovations on a large scale. In the decade ahead, the success of the U.S. labor market will be defined by how well it can equip the people displaced by technology with the skills that matter most. The challenge for policymakers, business leaders and educators is to deliver a smooth transition to the future labor market. Our modeling can aid in their success.



Chapter 1

Introduction

The current pace of innovation in digital technologies is unparalleled in history. As a core group of digital technologies evolves, including artificial intelligence, advanced robotics, mobile platforms, cloud computing and the Internet of Things (IoT), they are increasingly interacting in a way that rapidly expands their potential. As we embark on the next decade of innovation, the power of digital technologies will translate to all sectors of the economy. Perhaps inevitably, there are anxieties that this progress will negatively affect jobs and livelihoods, as workers from an increasingly wide range of backgrounds face a new form of digital competition.

The fear of automation troubles many in today's labor market, but widespread "technological unemployment" remains highly unlikely. Technology's relationship with the workplace is multi-faceted, dynamic and complex. Policymakers, business leaders and educators need to understand how this relationship will evolve in order to prepare for it. Workers can be complemented and augmented by technology, just as much as they can be displaced by it, and that depends on the specific nature of the jobs they do and the skills they have. In parallel, the economy also adapts and evolves to take advantage of the productivity gains presented by new technologies. With each new technological breakthrough, new ways are invented to consume the riches it brings, demanding new types of goods and services, which lead to new jobs and opportunities being created.

In this study, we took an innovative approach to modeling the holistic impact technological progress will have on jobs over the next decade. This includes taking into account the competing dynamics that occur in the labor market. We model the displacement of workers implied by new technological breakthroughs, such as reduced demand for translators amidst increasingly intelligent translation software, as well as the extra jobs created by productivity growth, such as the need for more software developers or restaurant service staff. Taking this approach offers a more complete picture of the challenges and opportunities that will unfold. How should workers prepare for the next decade of disruption? How should educators prepare their learning programs and companies design their training strategies? Where will the key pressure points emerge? This study provides unique insight into the changes that will occur in the labor market, to leave policymakers, business leaders and educators better informed to answer these questions. It also emphasizes the scale of the reskilling challenge the U.S. economy will face to make the most of the opportunities the next decade of technological progress will bring.

The report is structured in five parts. In chapter two, we summarize the most important literature on this topic and define how our approach will add to that literature. In chapters three and four, we set out the two core aspects of our modeling framework that estimate the extent of technological disruption to the labor market: the displacement effect and the income effect. In chapter five, we combine these two aspects to present our employment forecast for 2027, based on our assessment of the 2027 technology landscape. Finally, in chapter six, we use the Oxford Economics Skills Matching Model to analyze how displaced workers will respond to the challenges posed by technological advancement and what skills they must develop to find a new role in the future economy.

Box 1: Modeling the Long-Term Impact of Technology on Jobs

This study explored the impact of technology on jobs, at an unprecedented scale. We analyzed the reasoning of the "pessimists" and "optimists" in the existing literature. In recent years, much of the quantitative analysis has focused on which of today's occupations are most vulnerable to automation. But a very strong case is also made by prestigious economists, including David Autor, Darren Acemoglu, Maarten Goos and Alan Manning, who argue that productivity gains from technology lead to increased prosperity, which is a jobs-generator. A greater demand for workers to produce more and different goods and services than before, has historically outweighed the loss of jobs that automation implies.

Modeling these competing impacts is complex. We engaged with technology experts, drew on a variety of rich data sources—including detailed labor market, occupational, household and macroeconomic data—and developed a bespoke, multi-tiered modeling framework that enables us to forecast the shape of the labor market and also understand who moves where to reshape it.

Our methodology can be described in six parts:

Establishing the 2027 technology landscape
We began by combining comprehensive desk research and consultation with technology experts in Cisco and Oxford Economics to define the potential technological change that could take hold in the U.S. economy by 2027.

Analyzing productivity implications for workplace tasks
We explored the implications of these changes on jobs, using a targeted, interactive workshop with technology experts. The workshop used established scenario development techniques to focus on the impact technological change would have on the tasks and functions people perform in the workplace.

Modeling the implied "displacement effect"
Using detailed data on occupational characteristics from the O*NET database and the U.S. labor market, we explored the impact of our workshop outcomes on real jobs in the U.S. economy. Under our scenario, this revealed how fewer workers would be required to produce the same level of output, which reflects technology-driven productivity gains.

Modeling the long-term "income effect"
The productivity gains implied by our 2027 scenario will lead to faster economic growth, and the dividends of that growth will be spent on more goods and services in the economy. We used the Oxford Economics global industry model as a basis for estimating how the gains of productivity growth will be distributed across industries. We estimated the extra workers required to meet that demand in the context of our technology improvements.

Forecasting the 2027 labor market
We brought these two perspectives together to forecast the new shape of the labor market in 2027. We then used the Oxford Economics Skills Matching Model to predict how today's workforce will make that transition to the future. Our sophisticated model simulates how workers move through the labor market, away from redundancies and into vacancies, in response to changing conditions.

Analyzing the reskilling challenge
Our labor market projection enabled us to trace the moves workers will make to meet the needs of the 2027 economy. Based on the occupational background and skill level of those workers, we identified the reskilling challenges they will face in their new jobs, and examined what this means for the U.S. economy as a whole.

Chapter 2

The Impact of Technological Change on the Labor Market

We are living through an era of rapid and persistent technological breakthroughs in all aspects of life and business. As these technologies evolve and interact over the coming decade, they harbor great potential for the future. Business models will be transformed, industries reorganized, and economies will realize potentially large productivity gains. Such disruption also has substantial implications for the nature of work, with technology increasingly capable of performing the kinds of tasks upon which workers have traditionally prided themselves. In this chapter, we set out our assessment of how technological change will impact the labor market over the next 10 years.

2.1 WILL WE SEE JOBS DISAPPEAR?

Many futurists and technology experts predict a gloomy outlook for workers. In their seminal 2013 paper on the future of employment, Carl Benedikt Frey and Michael Osborne from the University of Oxford attempted to pin-point the occupations that would face the greatest "threats" from automation.[5] Using a combination of subjective expertise and statistical modeling, Frey and Osborne categorized all occupations in the U.S. labor market by the likelihood that they would be automated by artificial intelligence and mobile robotics in the next two decades. They found that 47 percent of workers in the U.S. economy were in jobs that they classified as "high risk" of automation. Frey and Osborne posited that many tasks that had previously been widely understood as impossible for robots to perform, outside the realm of codifiable computer reasoning, were increasingly in scope for artificial intelligence.

Frey and Osborne's study is not alone in painting a pessimistic vision of the future. MIT scholars Erik Brynjolffson and Andrew McAfee predict a future where humans will be outpaced by machines in their ability to adapt to changes in the workplace, leading to potentially large-scale unemployment.[6] A recent book by futurist Martin Ford paints a picture of increasingly powerful artificial intelligence making a wide array of jobs obsolete, with blue and white collar jobs disappearing from the labor market.[7] In his recent book, Jeremy Rifkin proposes that the notion of mass employment will eventually be confined to the past.[8]

5 Frey, C. B. & Osborne, M. A (2013) "The Future of Employment: How Susceptible are Jobs to Computerisation?" Mimeo. Oxford Martin School.
6 Brynjolfsson, E, & Andrew, M. (2014) "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies." New York.
7 Ford, M. (2015) "The Rise of the Robots", Basic Books, New York.
8 Rifkin, J. (2014) "The Zero Marginal Cost Society: The Internet of Things, the collaborative commons and the eclipse of capitalism", St Martin's Press, London.

The argument that robots will render workers obsolete is only considering one half of the picture. Technological progress is pursued, just as it always has been, as a means to enable us to produce more, better and cheaper goods and services with the same resources. There are functions, traditionally performed by humans that new technologies can perform faster, more consistently and/or to a higher quality. In adopting these new technologies, we can produce goods and services more efficiently. The other side of this coin is that the associated productivity gains drive a more prosperous economy, and a more prosperous economy demands more workers to feed its needs.

2.2 THE LONG-TERM EFFECT OF AUTOMATION ON EMPLOYMENT

Technological solutions can substitute workers, but they can also complement and enhance them. We have always looked for innovative tools and techniques to make us more effective or efficient at the things we do, from the early caveman and his sharpened rock to the cloud app that will do your company's accounts for you. But technology also complements worker skillsets, like a baseball coach drawing on the latest video analysis apps or an economist using more powerful statistical software.

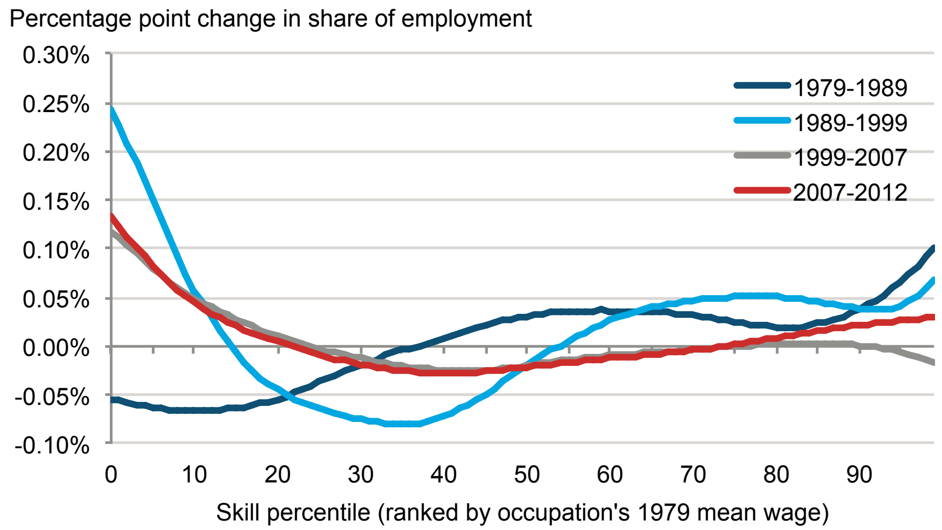
Technology is not designed to do people's jobs: It is designed to perform tasks. Any given job normally constitutes a wide array of varied tasks. For journalists, recording information and communicating it are two vital functions, and one could argue that these tasks are susceptible to automation. But as the old saying goes, "journalism is a people business," and there are other tasks, such as maintaining personal relationships and using judgement, that are also important to the profession. These tasks are consequently much more valuable. In fact, the journalist may well leverage new technologies to augment her skills in maintaining personal relationships. The tasks that cannot be so easily performed by machines, which tend to form an important part of almost all jobs, are generally complemented by them and become even more valuable when combined.

Technological progress perpetually improves our productivity in getting tasks done, but some tasks are easier to automate than others. Research by David Autor, Frank Levy and Richard Murnane, identified that in this new age of technological progress, it is workers performing *routine tasks*—whether they be characterized as manual or cognitive tasks—that are most exposed to automation.[9] These might include routine administrative work like writing standard letters of correspondence, or routine production work like judging the qualities of components moving along the assembly line. Analyzing historical trends in the labor market, Autor went on to identify a "hollowing out" effect in which mid-skilled workers appeared to be disproportionately affected by technological innovation.[10] Occupations in the bottom and top end of the skills spectrum (according to 1979 job-classifications) saw their share of the workforce rise, whereas the share of mid-skilled occupations shrank. In fact, Autor's later work found that as the decades went by and technology became increasingly powerful, this technological displacement was affecting occupations further and further up the skills spectrum. We recreated Autor's chart using data on the U.S. labor market as a basis for our analysis—as presented in Fig. 4.

9 Autor, D. H., Levy, F. & Murnane, R. J. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," The Quarterly Journal of Economics, 118(4): 1279–1333.

10 Autor, D. (2015) "Why Are There Still So Many jobs? The History and Future of Workplace Automation" Journal of Economic Perspectives, Vol. 29, no. 3, Summer, pp. 3-30.

Fig. 4 Historical shifts in employment across the skills spectrum, 1979-2012 Change in share of total employment by percentile of the workforce (percentiles based on occupations ranked by 1979 mean log wage).



Source: Oxford Economics, American Community Survey, IPUMS

Once viewed through the prism of tasks, the implications for jobs become more nuanced. A study by Melanie Arntz, Terry Gregory and Ulrich Zierahn for the OECD in 2016,[11] revisited Frey and Osborne's analysis, but redefined the concept of automatability as one that applies to the tasks people perform rather than their job title. For example, Frey and Osborne identify "retail salespersons" as having a 92 percent probability of "computerization." When the OECD study broke this occupation down into its component parts, they found that only four percent of retail salespersons could perform their jobs with neither "group work" or "face-to-face interaction," which are two aspects that Frey and Osborne defined as non-automatable engineering bottlenecks. As a result, the OECD's analysis led to a more conservative estimate that only nine percent of U.S. workers were at high risk of automation. When they analyzed technology's impact on the tasks people perform, rather than generalizing to the jobs they do, they saw a completely different picture.

In fact, as technological innovation lowers the cost of production, it has a positive impact on people's "real" wealth. The productivity gains from technology mean lower costs. As companies compete, these cost savings are passed on through lower prices, and lower prices mean more money left in the consumer's pocket, which he or she can choose to spend on other goods and services. The impacts of technological breakthroughs are recycled through the economy to stimulate a greater demand for workers to produce more goods and services. This pattern has borne out repeatedly through history.

11 Arntz, M., Gregory, T. & Zierahn, U. (2016), "The Risk of Automation of Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris.

This rising trend in employment does not necessarily mean higher wages or better quality work. The U.S. labor market has been characterized by wage stagnation and falling job security for many in recent decades. In this study, we do not address these policy concerns directly. Rather we shed light on the changes that are likely to take place in the labor market over the next decade and the skills workers will need to adapt to deal with them. In doing so, we provide policymakers, business leaders and educators with a new tool to deal with the social challenges that technological displacement may invoke.

2.3 THE OXFORD ECONOMICS APPROACH

In this study, we provide a unique and innovative perspective on the long-term impact of technological change on the labor market. We go beyond the scope of the existing literature, which identifies the "jobs at risk of automation," by combining a "bottom-up" analysis of the tasks that will be automated with a "top-down" analysis of the economic growth and job creation that the same technological progress will bring about. To do this, we modeled two important effects:

1. **The displacement effect:** Technological change will manifest itself as *labor saving innovations*. To what extent will the next decade's technological progress "displace" workers from performing tasks that technology can now do better? Technology can be applied to different tasks in different ways, and some will be more susceptible to automation than others. The "displacement effect" is the aggregation of labor savings across the labor market.

2. **The income effect:** Labor saving innovations from technology mean lower production costs. In a competitive economy, these cuts are passed onto the consumer through lower prices and this leads to an increase in their real spending power. As they spend this dividend, it generates demand for employment elsewhere in the economy. The increase in jobs that results is captured by the "income effect." We use the Oxford Economics global industry model to estimate where this demand will be directed over the next decade, as a result of technology-driven productivity gains and other macroeconomic trends, such as demographics, investment and trade.

In reality, there is also a third effect at work under our technology scenario, which could be called the "substitution effect." As technology causes some prices to drop further than others, consumers may be attracted to purchase more of the cheaper goods or services produced, and this would influence where in the economy new jobs are created. The substitution effect does not factor into our framework because, to the extent that it occurs, Oxford Economics' view on it is captured in the industry Gross Value Added (GVA) forecasts.

In the following chapters, we set out our approach to measuring the displacement effect and income effect before going on to explore how they will alter the shape of the U.S. labor market.

Chapter 3

The Displacement Effect

The premise of our analysis is a 2027 technology landscape that foretells a dynamic decade of great technological leaps forward. This landscape is illustrated in detail in Annex 1. It sets the scene that, by 2027, a constant stream of data is being generated about every aspect of life and business, and increasingly powerful computers have emerged to analyze it. Innovations in high tech manufacturing, mobile technology and artificial intelligence have considerably enhanced what human beings are capable of. The futurists are right that this will make certain workers in today's economy redundant at performing a certain set of tasks, in the event that technology can do them cheaper or to a higher standard. But how will such dramatic technological progress change the work we do (and don't do) over this period?

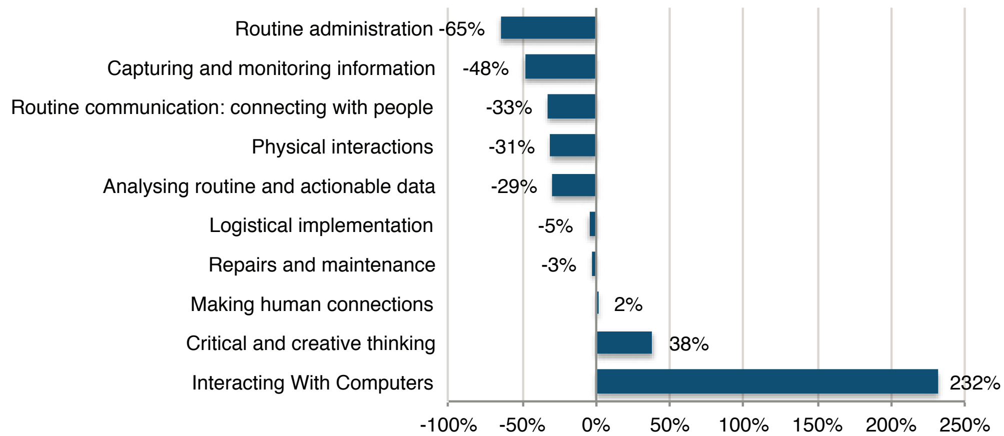
In this chapter, we detail the approach we took to modeling the displacement effect of technological change in the U.S. labor market over the next decade. We used highly detailed datasets from the O*NET online resource as a basis for our analysis. This provides insights into the workplace tasks different occupations carry out and the skills they require. Further information on O*NET and how we used it can be found in Annex 4. We worked with experts to define the advances technology will likely make over the next 10 years, and what that will mean for their ability to perform the everyday tasks that characterize our working environment. We used labor market statistics from the Bureau of Labor Statistics to derive the implications for these task-based changes on jobs across the U.S..

3.1 HOW WILL TECHNOLOGICAL ADVANCES AFFECT WORKPLACE TASKS?

We engaged with technology experts to develop a detailed hypothesis about the likely progress technology will make over the next decade in being able to perform workplace tasks. We brought experts from a variety of technical backgrounds together to form a collective judgement, via an interactive workshop, on the future capabilities of a range of technologies, including artificial intelligence, advanced robotics and mobile platforms. They were asked not only to consider how far technology will progress, but "the extent to which the output we produce today could be produced by fewer workers." The participants were asked to consider the likely rate of adoption of those technologies across the economy as part of their estimate. In doing so, we were able to systematically produce a set of stylized assumptions about the potential productivity gains of new technologies in the next decade.

The workshop was designed to feed qualitative assumptions directly into our quantitative modeling framework. The workshop assumptions were formed around an existing, and comprehensive, typology of 41 workplace tasks, compatible with the O*NET database. The productivity gains implied for workplace tasks by our expert workshop are presented in Fig. 5, with the task implications aggregated into 10 task clusters. Routine administrative tasks were determined to be most susceptible to labor saving technological innovations, followed by capturing and monitoring information, routine communication and physical interactions. Of the seven task clusters in line for a negative displacement effect, repairs and maintenance was deemed to be the least likely to be automated. Making human connections, critical and creative thinking and interacting with computers, were three task clusters deemed to require more workers over the next decade as a necessary corollary of achieving the automation of the other workplace tasks.

Fig. 5 Displacement effect by task cluster (Estimated change in aggregate worker hours required to perform this task)



Source: Oxford Economics Analysis

The net negative impact on the number of workers required to perform today's tasks means a substantial productivity gain across the labor market. In Box 2 and Box 3 we summarize the justifications made by our expert panel to support these results.

Box 2. Tasks in Line for the Largest Labor Productivity Gains

Our workshop produced estimates of the likely productivity impact of technological change for 41 workplace tasks, arranged into 10 task clusters. Below, we list the five clusters in which our expert panel expect to see the greatest productivity gains and summarize their reasoning.

Routine administration: 65 percent net reduction in labor input.
(Includes scheduling work, documenting information)

- Artificial intelligence (AI) and data analytics have already begun to transform back office functions and will be capable of heavily automating many administrative functions in the next decade, affecting a large number of jobs. Human judgement will still be required to trade-off and prioritize competing tasks and commitments, which means workers are likely to still be required to perform administrative tasks of a sort, interacting with computers rather than being completely replaced by them.

Capturing and monitoring information: 48 percent net reduction in labor input.
(Includes inspecting equipment, monitoring resources, obtaining data)

- With the coming of age of the Internet of Things (IoT) and data analytics, many monitoring tasks are expected to be heavily automated over the next decade. Data collection will become much less burdensome and will thus require fewer data-collectors. Machines will also become better at not just collecting data but identifying what data is relevant to specific questions or applications, although that still requires human involvement to a large extent.

Routine communication with people: 33 percent net reduction in labor input.
(Includes communications with people outside an organization, teaching and training)

- Communication with others is a valuable human skill that is only expected to become more valuable in the future. Technology will make communication more efficient, meaning we can do more of it at a higher quality and waste less time in routine communication.

Physical interaction: 31 percent net reduction in labor input.
(Includes operating vehicles and mechanical devices, moving objects)

- Significant progress will be made in robotics, meaning they can operate in tighter and less predictable environments. Intelligent drones, autonomous vehicles (not just road-vehicles but also warehouse and other internal vehicles) and advanced robotics are expected to make rapid progress though cost factors may still slow down widespread adoption.

Analyzing routine actionable data: 29 percent net reduction in labor input.
(Includes estimating the quantifiable characteristics of things, evaluating compliance with standards, controlling machines and processes and analyzing data)

- With improvements in analytics and pattern recognition software, many routine tasks such as identifying objects, controlling machines and estimating the quantifiable characteristics of things are expected to become programmable and therefore automatable in the next 10 years. This has implications for a broad range of jobs across the economy, but roll out will be slowed down by the complexity of applying such techniques to the infinite complex functions that shape our world. Many tasks are still expected to require a human level of trust in the next 10 years, including verifying the work computers have done.

Box 3. Tasks in Line for the Smallest Labor Productivity Gains

Below, we list the five task clusters our expert panel identified as being in line for the smallest productivity gains from technological change over the next decade and summarize their reasoning.

Logistical implementation: 5 percent net reduction in labor input.

(Includes staffing organizational units, organizational planning, coordinating others)

- Big data and AI are expected to significantly reduce the amount of effort required to coordinate the activities of others and develop objectives and strategies. As technology makes organizational and logistical tasks easier, as well as cheaper and more competitive, it may employ fewer workers in its own right but become a component of many more people's jobs, offsetting the labor savings in the macro sense.

Repairs and maintenance: 3 percent net reduction in labor input.

(Includes repairing mechanical and electronic devices)

- More devices, everywhere, means a greater demand for repair and maintenance. But the Internet of Things (IoT) makes the burden much more efficient. For example, remote monitoring of car performance detects potential problems before they get worse.

Making human connections: 2 percent net increase in labor input.

(Includes resolving conflicts and negotiating with others, developing and building teams, establishing and maintaining personal relationships, motivating people, caring for others)

- Significant efficiency savings are expected in routine, predictable communications but consumers will place a premium on human service and pay more for it. Expert consultants will work with technology to provide a better service and the demand for experts will continue to grow as the world becomes more complex. For managers, AI and analytics may play a bigger role in setting workplace standards, but managers will work with technology to become better at their job, building teams for optimal performance, motivating subordinates and making decisions.

Critical and creative thinking: 38 percent net increase in labor input.

(Includes judging the qualities of things, decision making, thinking creatively)

- Artificial intelligence will make headway in a number of traditional creative or critical thinking tasks in the next decade, but will be slow to replace humans. More likely, humans will leverage AI to make better informed judgements and ideas.

Interacting with computers: 232 percent net increase in labor input.

(Refers only to interacting with computers)

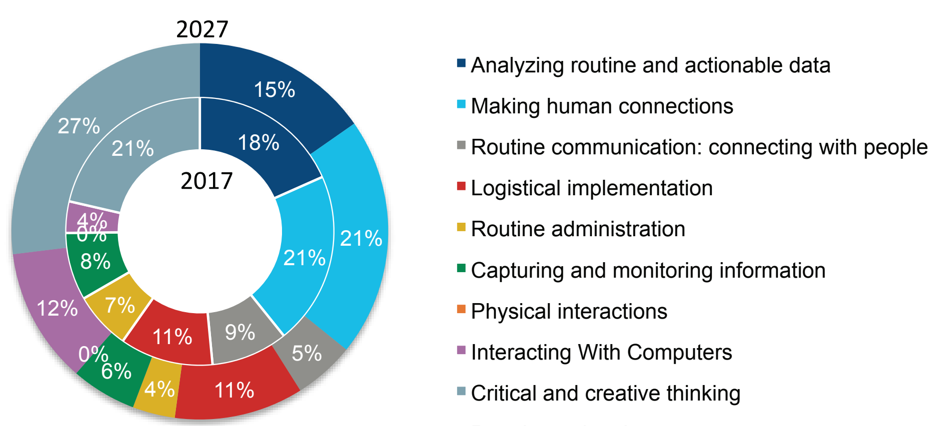
- Almost all jobs will require at least a basic level of interaction with computers. In some industries where Information Communications Technology (ICT) skills had traditionally been irrelevant, they are now business critical; for example, in healthcare, utilities, logistics and retail.

3.2 OCCUPATIONS: HOW DOES DISPLACEMENT AFFECT JOBS?

To understand how these efficiency savings would play out, we developed a detailed picture of who does what in the U.S. economy. Using the O*NET database, we calculated the task-profile of over 800 occupations and modeled the impact that the displacement effect described above would have on the working lives of the people in those occupations. This approach is beneficial in that it does not attempt exhaustively to define the myriad ways in which new technology will evolve and apply to industry over the next 10 years. Instead, we base our assumptions on the core capabilities technology will develop and assume that those capabilities are transferable across all industries that require them. For example, if sophisticated cameras and pattern recognition software could be applied in factories to monitor materials passing along a production line, we assume they could also be applied in an agricultural context, in warehousing, or sports activities.

We estimate the impact of technology's displacement effect on every single occupation in the U.S. labor market and aggregate to assess the implications. To elucidate the modeling process, we have presented the displacement effect for two specific case studies below: a lawyer and a heavy truck driver. For the lawyer, Fig. 6 presents the task profile that defines her job in 2017, compared to the adjusted task-profile implied by our 2027 technology scenario. The lawyer is characterized by a large requirement for analyzing routine and actionable data (over and above what she may delegate to a paralegal or legal secretary), making human connections, and critical and creative thinking. There are also smaller requirements for routine communications, routine administration and capturing and monitoring information. In our 2027 scenario, we see technology freeing lawyers up to be able to put their unique skillset to greater use. As artificial intelligence applications reduce the time and effort required to complete routine tasks, such as discovery and drafting correspondence, lawyers can divert more time to more valuable activities like critical and creative thinking and improving the quality of the services they can provide. The lawyer spends about 30 percent more time on critical and creative thinking in 2027, and about 30 percent less time doing routine administration, routine communication and analyzing routine data.

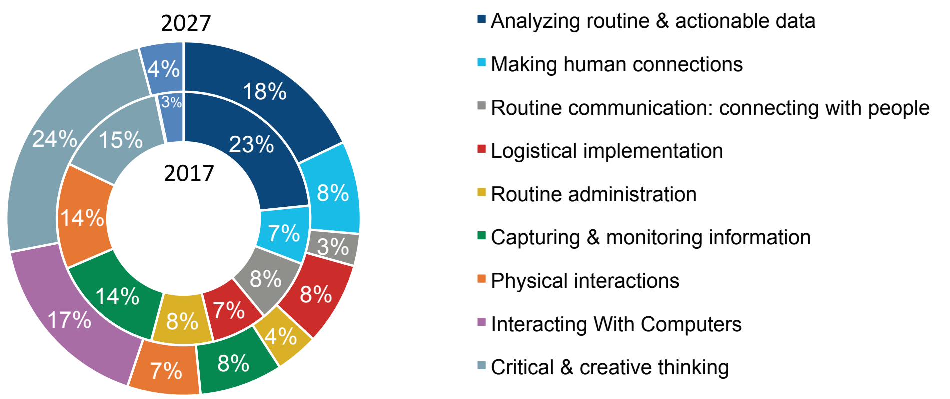
Fig. 6 Change in lawyer's task profile from 2017 to 2027, following the displacement effect



Source: Oxford Economics

The heavy truck driver, who will face great competition from increasingly capable automated vehicles in the next decade, will see her job evolve to the realities of our 2027 scenario. In 2017, the heavy truck driver spends much less time making human connections and critical and creative thinking than our lawyer, and much more time engaged in physical interactions, repairs and maintenance, and capturing and monitoring information. By 2027, her job profile will transform as technology reduces the demands on the driver to operate the vehicle in the traditional sense. Many of the tasks that are important to heavy truck driving in 2017 become relatively less burdensome: analyzing routine actionable data, routine communications with people, capturing and monitoring information and physical interactions. In the end, this results in a significant reduction in demand for truck drivers. But for the substantial number who remain, and who are able to upgrade and adapt their skills in the right way, their focus shifts to interacting with computers and, in connection with that, engaging in more critical and creative thinking than before.

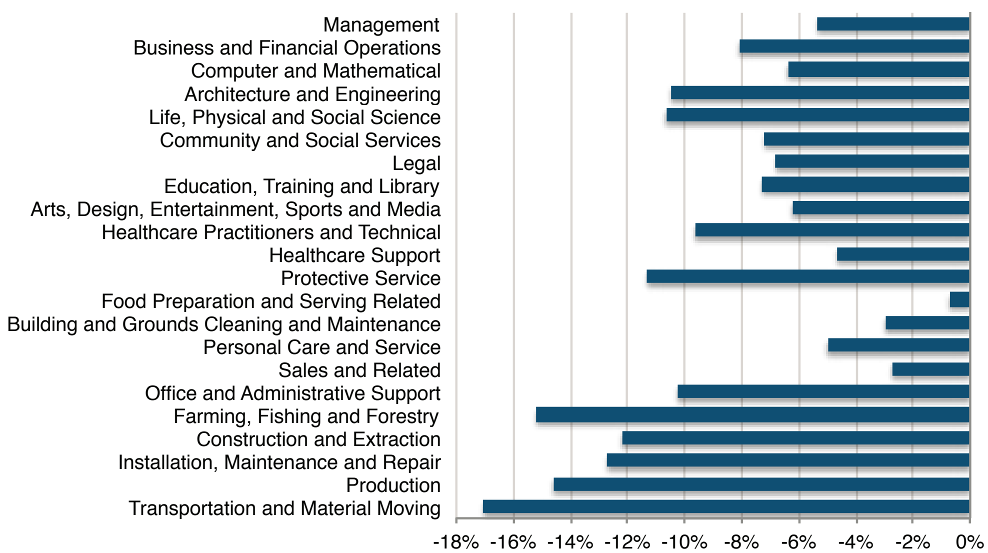
Fig. 7 Change in truck driver's task profile from 2017 to 2027, following the displacement effect



Source: Oxford Economics

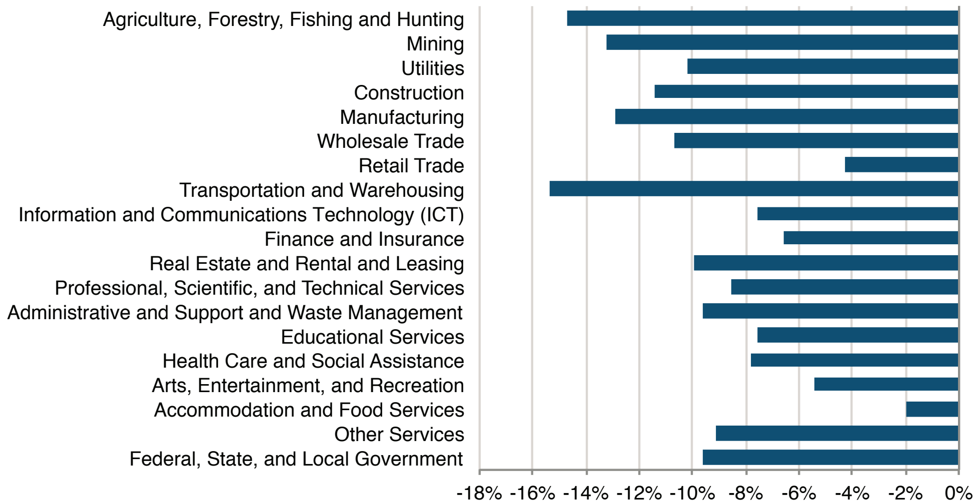
Aggregating up the displacement effect across the labor market reveals who is most vulnerable to the next decade of technological change. In Fig. 8, the displacement impact is aggregated into 22 occupational groups. Transportation and material moving jobs, like truck drivers, crane operators and aircraft cargo-handlers, are most heavily disrupted by our technology scenario. These jobs are not eliminated entirely; many workers will evolve, retrain and remain in their jobs. But our scenario implies a 17 percent displacement of these workers, who are typically characterized by tasks such as operating mechanized equipment and performing general physical activities, which are ripe for automation. At the other end of the scale, food preparation and serving jobs are least disrupted, with only a 0.7 percent reduction. This group includes cooks, bartenders, hosts and hostesses, and tends to require tasks that are less automatable, such as assisting others, exploiting interpersonal relationships and creative thinking. The breadth of technological applications over the next decade means there are significant implications for highly paid and specialized workers too. Our scenario suggests more than five percent of managers would be displaced and more than eight percent of workers in business and finance positions.

Fig. 8 Displacement Effect by Occupational Groups
(Percentage change in full time equivalent (FTE) employment)



Source: Oxford Economics

Fig. 9 Displacement Effect Across Industries
(Percentage change in full time equivalent (FTE) employment)



Source: Oxford Economics

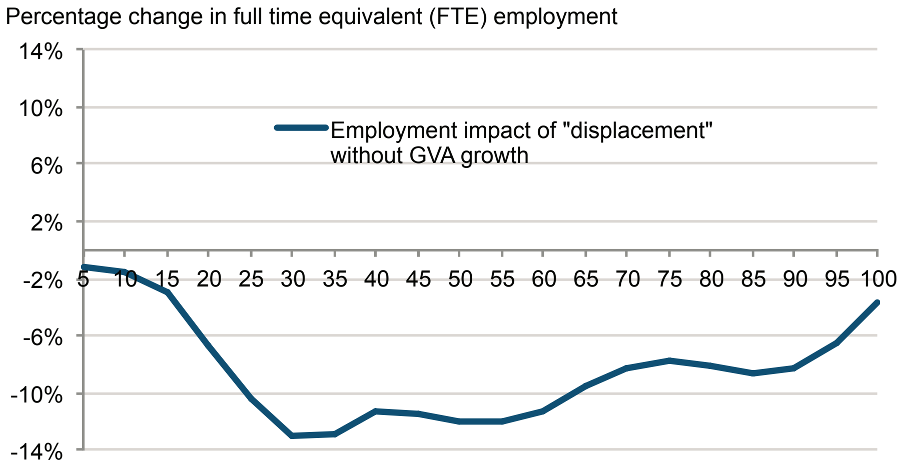
3.3 INDUSTRIES: HOW IS THE EFFECT DISTRIBUTED ACROSS THE ECONOMY?

We analyzed the implications for different industries by mapping the occupational impacts across the economy. We used detailed industry-occupation matrices to map those occupational impacts across 19 industries, as presented in Fig. 9. The greatest workplace disruption is experienced in the transportation and warehousing industry. These jobs continue to exist in our scenario, but more than 15 percent of full time equivalent (FTE) jobs are displaced. This is followed closely by jobs in agriculture, forestry, fishing and hunting (15 percent), mining (13 percent) and manufacturing (13 percent). Put differently, these are the industries we identify as being those in line for the greatest productivity gains from labor-saving technologies over the next decade. At the other end of the scale, jobs in retail (4 percent) and accommodation and food services industries (2 percent) are expected to see the smallest labor productivity gains.

3.4 RESULTS: THE DISPLACEMENT EFFECT

Our assessment of the displacement effect aligns with the literature on jobs at risk of automation. To assess the validity of our modeling outputs, we compared our findings with other high-profile studies in this field. Our model found that the displacement effect in isolation would affect 8.4 percent of workers by 2027. This equates to more than 11 million workers, which is very close to the OECD's estimate of the number of jobs "at high risk of automation." The OECD study also employed a task-based approach but used a different occupational dataset and modeling methodology. Our results, like the OECD's, suggest the true displacement effect that can be expected from technological change in the next decade is much smaller than the headline figures of Frey and Osborne.

Fig. 10 How technological change will affect workers in low, mid and high-skilled jobs: Displacement effect
Projected change in employment by percentile of the workforce (presented as five-percentile aggregates, ranked by 2015 mean wage as a proxy for skill level).



Source: Oxford Economics

Behind this headline number, our analysis also shows that the displacement effect, as we define it, will be very widespread. The impact of new technology will be felt across the entire U.S. labor market over the next decade. Nevertheless, some workers will see a much greater change than others. In chapter 2, we recreated David Autor's chart of the historical shifts in employment that have occurred across the skills-spectrum in the U.S. labor market, driven by three decades of technological change. We updated this chart in order to illustrate what the next ten years could look like in terms of the percentage change in employment for each percentile of the labor market. Fig. 10 shows how the displacement effect, which implies large losses in mid-skilled jobs between the 20^{th} and 40^{th} skill-percentiles of the labor market, when assessed in isolation. This cohort includes jobs like highway maintenance workers, credit authorizers and parking enforcement workers.

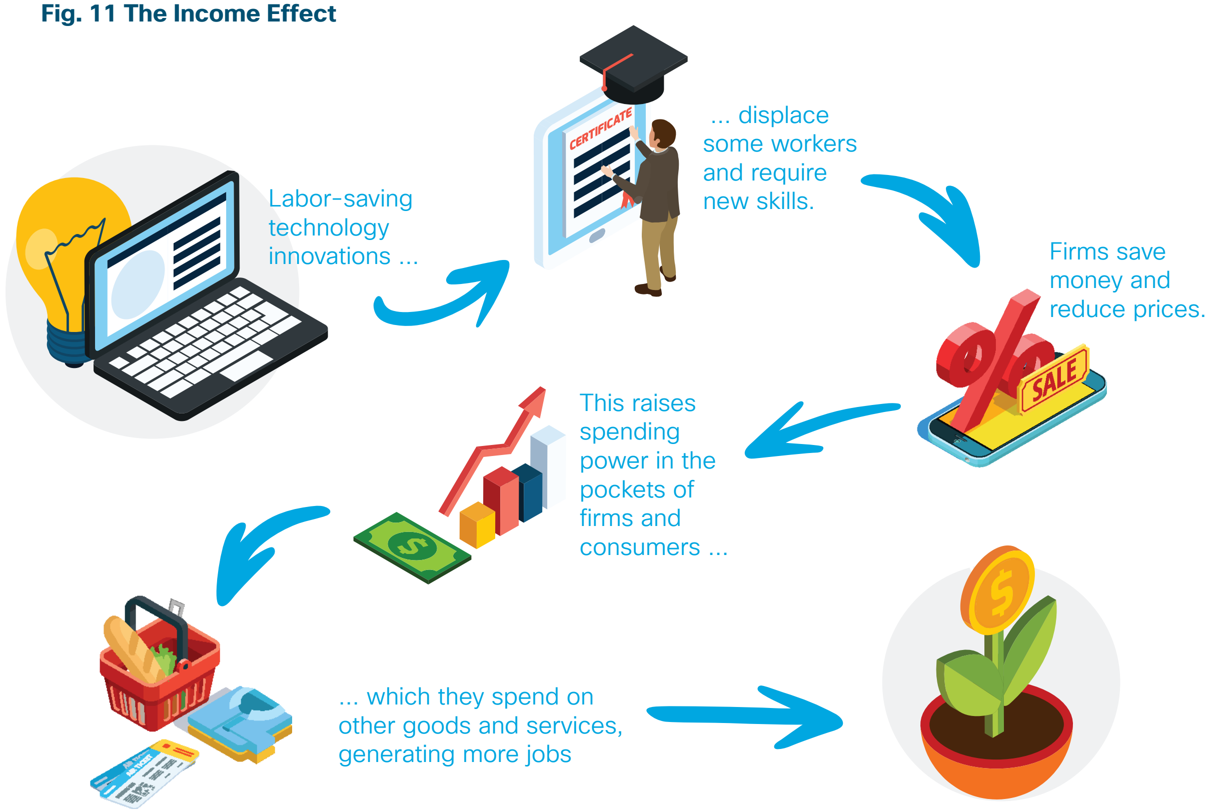
The technological achievements expected by our panel of experts over the next decade will considerably shift the status quo. As companies invest in new tools and software and adapt their business practices to leverage new opportunities in the marketplace and in their supply chains, many workers will find that the contribution they used to make becomes redundant. But this displacement effect on its own tells only half the story. In the real world, as these same technological changes are being realized, they will spur productivity growth, an expansion in real wealth and new demands for goods and services elsewhere. Those surplus workers, if they can bridge the relevant skills-gap and make the transition to a new occupation, will be faced with multiple opportunities to continue to add value in the economy. In the next chapter, we explore where those opportunities will arise.

Chapter 2

The Income Effect

Technological progress has a dynamic relationship with the labor market, shifting incentives, altering prices, changing consumption habits and redistributing demand throughout the economy. The displacement effect set out in the previous chapter represents how the productivity gains of new technology will squeeze out workers from their current jobs. But to stop here leaves an unbalanced impression of the impact new technologies have on the world of work. In this chapter, we go one step further to assess the macroeconomic consequences of the technological progress we expect to take place over the next decade and the boost they will give to employment. This is where our analysis departs from the existing literature in providing a more holistic view of the impact of technological change on jobs.

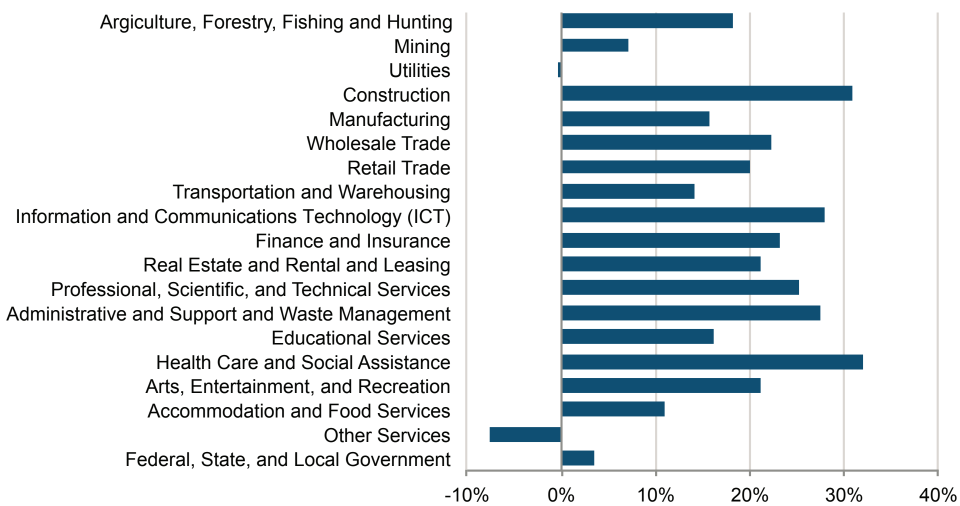
Fig. 11 The Income Effect



4.1 WHERE WILL THE INCOME EFFECT CREATE NEW JOBS IN THE ECONOMY?

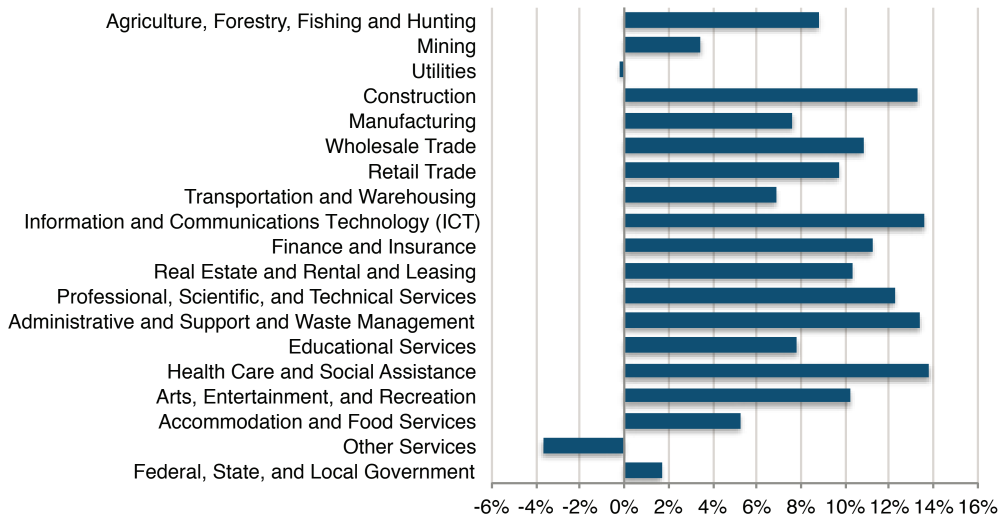
The income effect is derived from an increase in spending power. It is therefore skewed towards those sectors where the extra money will be spent. We draw on 10-year Oxford Economics U.S. industry forecasts to identify where this increase in demand will occur. The forecasts embody the long run productivity growth expected in the U.S. economy. It therefore incorporates the essence of the 2027 technology landscape from a macroeconomic perspective, albeit including other growth drivers too, such as energy price cycles and demographic trends. For the U.S. economy, over the next decade, an anticipated surge in the construction and healthcare industries stands out as a key driver of growth. But there is also strong demand across service industries, including Information Communications Technology (ICT) services, and in manufacturing and agriculture.

Fig. 12 Forecasted GVA growth across U.S. sectors (2017-2027)



Source: Oxford Economics

Fig. 13 Income effect on industries (Percentage change in full time equivalent (FTE) employment)

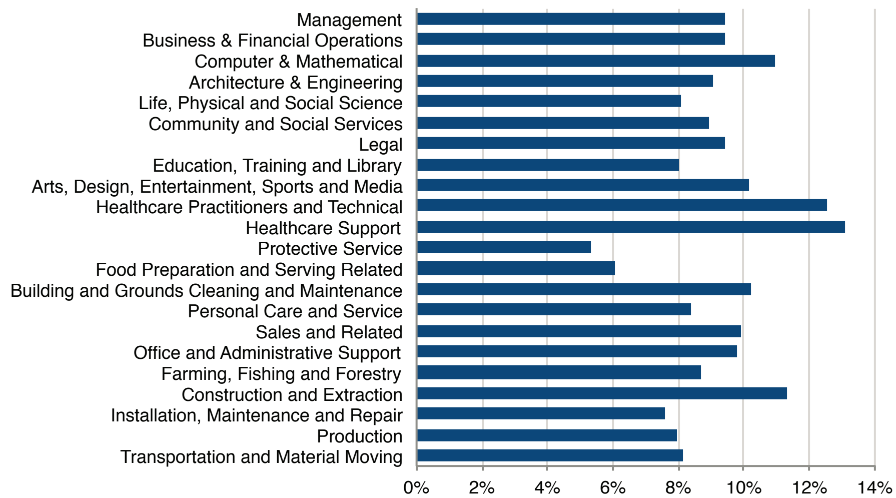


Source: Oxford Economics

4.2 INDUSTRIES: WHAT IMPACT WILL THIS SURGE IN DEMAND HAVE ON JOBS?

To estimate the employment implications of the industry Gross Value Added (GVA) growth profile, we must control for productivity improvements, which are captured separately via our displacement effect. To do this, we assess the employment implications of our GVA growth projections, assuming that the ratio of labor to capital in production remains fixed at 2017 levels. This assumption is imposed so as not to double count the productivity gains expressed via the displacement effect. Fig. 13 shows the impact on employment across the economy. Four industries stand out. The information sector, which includes ICT services, sees a surge in full time equivalent (FTE) employment of around 14 percent. This is matched by a growth in job demand in healthcare, administrative and support services, and construction. We expect to see a net decline in demand for workers in only two other sectors, utilities and other services, which includes personal and laundry services for example. In these sectors, there is a fall in demand forecasted, which accentuates the reduction in labor implied by the displacement effect. The income effect is associated with an almost 4 percent drop in employment in the industry labeled “other services” over the next 10 years.

Fig. 14 Income effect on occupations (Percentage change in full time equivalent (FTE) employment)

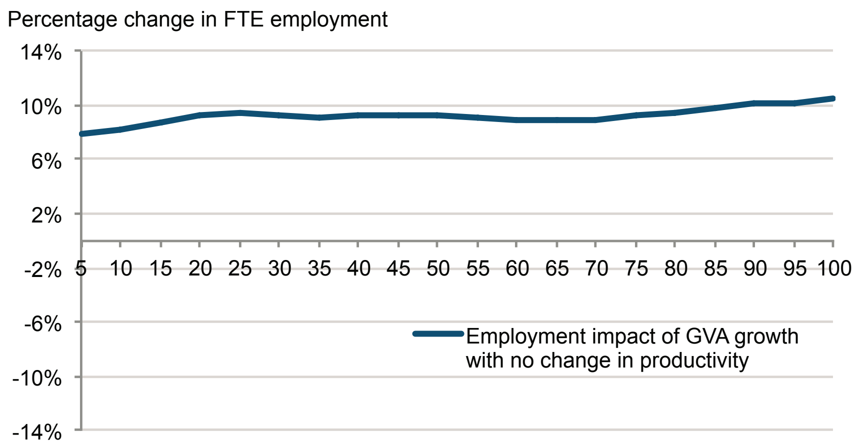


Source: Oxford Economics

4.3 OCCUPATIONS: HOW DOES THE INCOME EFFECT HIT DIFFERENT OCCUPATIONS?

Unlike the displacement effect, we estimate the income effect from the top-down, starting with the industry level forecasts. We derive the impact on occupations based on the balance of jobs within each industry, using industry-occupation data from the U.S. Bureau of Labor Statistics. Fig. 14 shows the income effect's positive impact on 22 occupational groups. Once again, we see construction, computing and healthcare jobs on the rise, via increased spending in these areas. There is also strong growth in demand for sales jobs, finance, and management, of close to 10 percent. Workers in protective services (for example, physical security) and food preparation are in line for a lower return from the income effect.

Fig. 15 How technological change will affect workers in low, mid and high-skilled jobs: Income effect Projected change in employment by percentile of the workforce (presented as five-percentile aggregates, ranked by 2015 mean wage as a proxy for skill level).



Source: Oxford Economics

4.4 RESULTS: THE INCOME EFFECT

The income effect pulls in the opposite direction to the displacement effect. We reapply the chart used in previous chapters to show how the income effect boosts demand for mid-skilled jobs. Aggregating the income effect, alone, across the economy leaves a positive impression on employment overall, by 2027.

The power of the income effect can be seen in real world examples. For instance, the U.S. supermarket and grocery sector* has been subject to a mass roll-out of automated self-service checkouts and online shopping in the past decade. But in the same period, employment has risen by almost four percent, and sales related jobs as a whole over that period have risen by three percent, resulting in only a slight reduction in their overall share of the labor market. This example shows how technological advances and automation of certain tasks can coincide with a net increase in jobs. Innovations lower prices and consequently increase the demand for services from that sector. The technology takes certain routine tasks away from workers and also frees them up to do other, often more valuable things instead. In our modeling framework, we are able to estimate the displacement and income effects of technological change independently. But in reality, as in the U.S. retail sector, the two effects do not occur in isolation. In fact, they are two sides of the same coin. In the next chapter, we combine the displacement and income effects to develop a balanced picture of the likely impact technology will have on the future of the U.S. labor market.

* Supermarket and grocery sector pertains to NAICS code 445110

Chapter 5

What Will This Mean for Jobs?

The relationship between technology and the labor market is complex, but by combining our analysis of the displacement and creation of jobs that technological progress will entail, we can forecast how the labor market will adapt. This insight is crucial for policymakers and other important stakeholders to understand where the pressure points and opportunities will arise throughout this disruptive period. Our detailed labor market forecast shows, in granular detail across 800 occupations and 19 industries of the economy, how the labor market will evolve over the next decade.

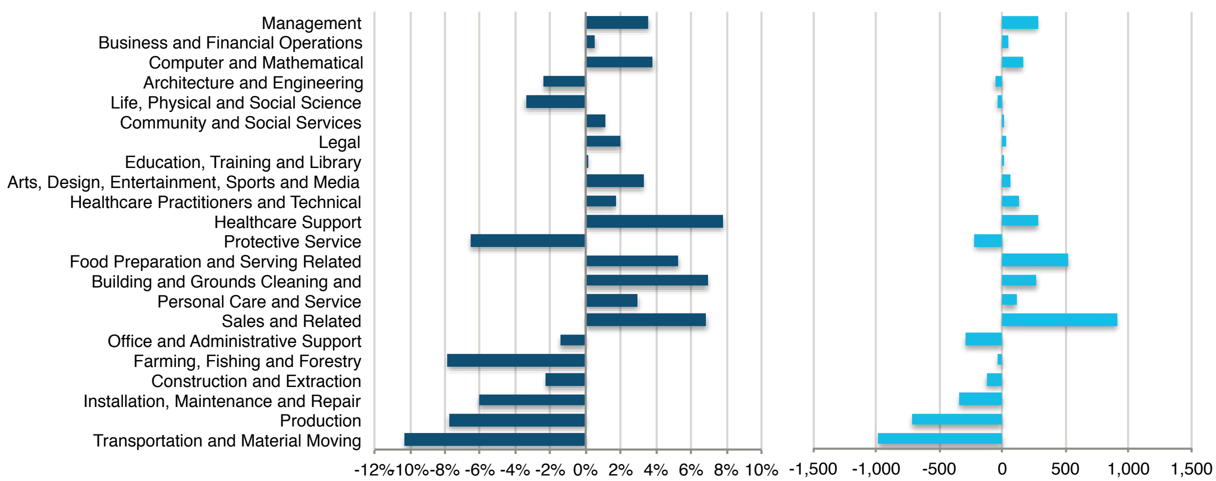
In addition to our labor market forecast, we used the Oxford Economics Skills Matching Model to understand how today's workers will adapt and respond to this change. By using rich datasets on historical job moves and occupational characteristics, we simulated the ways in which every worker displaced by our technology scenario would plot their way through the labor market to find new work, and how every job vacancy would find someone to fill it. Our model enables us to identify who is likely to move where, in order to make the prospects of the 2027 technology landscape possible. In this chapter, we set out the results of that analysis.

For modeling purposes, our focus is squarely on the disruption caused to the labor market's status quo. The labor market is constantly dealing with a regular rate of "churn" as workers move up and down the career ladder, in and out of the labor market and across occupations and industries for a variety of reasons. This is essentially a matter of individual choice and is built into the baseline of our labor market expectations. Over and above this regular churn, the disruption caused by technology will affect workers through no choice of their own. For modeling purposes, we assume workers are able to keep up with the changes in technology required to do their job. Our focus is on what happens to these workers, at the margins, that are forced out of their job or enticed to take a new one. This group provides a key indicator of where the pressure points will emerge over the next 10 years.

5.1 OCCUPATIONS: WHO IS IN DEMAND IN 2027?

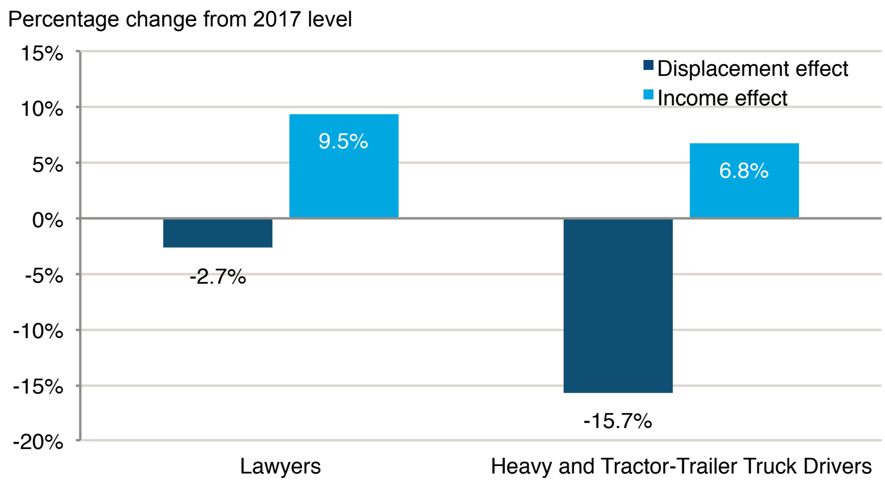
In the next decade, we will see a boom in technology jobs, but this is only one of many growth areas. Over the next 10 years, we forecast a considerable reconfiguration of the U.S. labor market around the opportunities created by technological change. Combining the displacement and income effects, we estimate a four percent increase in demand for workers with a computing and mathematical background. But there is also an eight percent increase in healthcare support jobs, and a seven percent increase in building and maintenance jobs, and sales. On the other hand, employment in transportation occupations is expected to shrink by more than ten percent, and production jobs by almost eight percent.

Fig. 16 2027 Employment forecast by occupational group (Left: Percentage change in full time equivalent (FTE) employment (%), Right: Absolute change in FTE employment (thousands))



Source: Oxford Economics

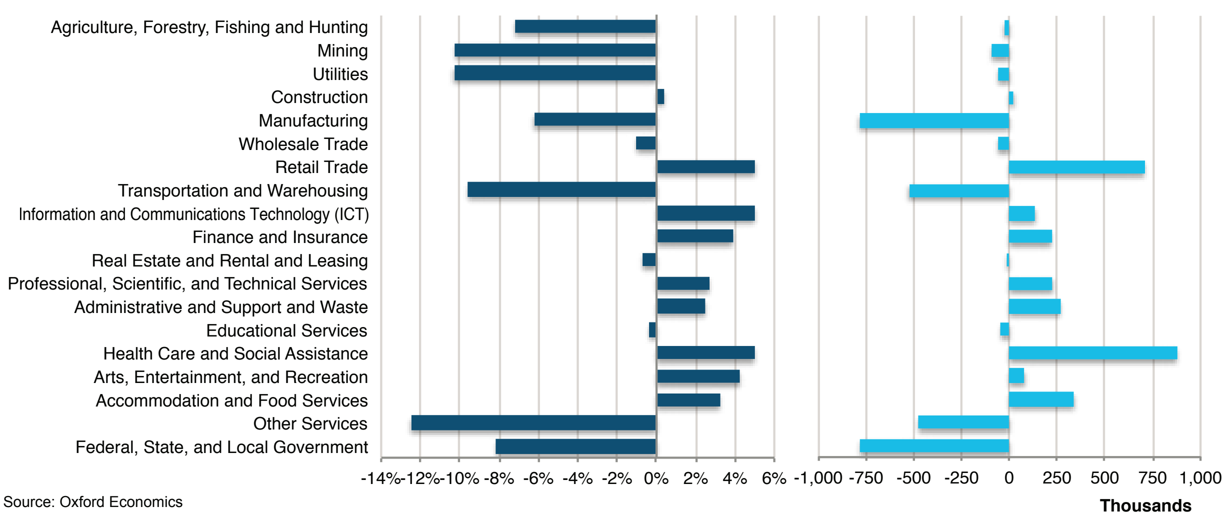
Fig. 17 Change in employment for lawyers and truck drivers



Source: Oxford Economics

Our forecast provides granular insights into the implications for different occupations. Fig. 17 returns to our case studies. Demand for lawyers is expected to grow in spite of the labor-saving innovations in technology, as the expanding economy demands more legal services. On the other hand, heavy truck drivers will experience a significant net reduction as the gains made by automated vehicles outweigh the increase in demand for haulage services. For truckers, this is the equivalent of an 8.9 percent net reduction in employment.

Fig. 18 Industries: Employment forecast by industry (Left: Percentage change in full time equivalent (FTE) employment (%), Right: Absolute change in FTE employment (thousands))

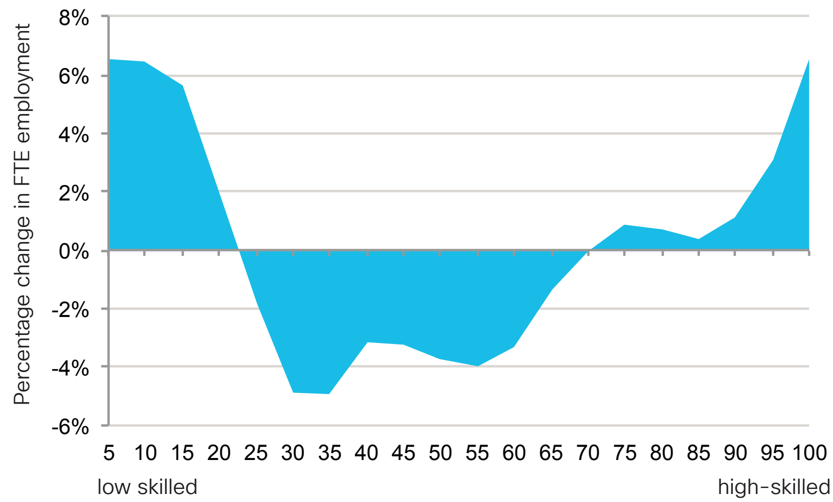


Source: Oxford Economics

5.2 INDUSTRIES: WHERE ARE JOBS BEING CREATED AND LOST?

The employment picture that emerges from our forecast is not one that is dominated by the ICT industry. Roughly half of industries see an increase in demand for workers, and half see a decrease as displaced employees are recycled through the labor market. The construction industry, retail, professional, finance and information services are all net recruiters, while the government sector, utilities, manufacturing, transport and agriculture reduce their headcounts.

Fig. 19 How technological change will affect workers in low, mid and high-skilled jobs Projected change in employment by percentile of the workforce (presented as five-percentile aggregates, ranked by 2015 mean wage as a proxy for skill level).



Source: Oxford Economics

Our analysis suggests that the "hollowing out" of the labor market is likely to continue at a similar rate as in the past two decades. There are no signs of the acceleration in this trend that many futurists have predicted. We combined our estimates of the distributional impacts of technological change across the skills spectrum from the displacement and income effects. The results show that the heaviest burden of technological change continues to fall on mid-skilled workers in general, while new jobs are created for those with lower and higher skills. This will mean continued hardship for many in the labor market. Those with skillsets least compatible with the future demands of the workplace may see their wages stagnating and struggle to attain security in their employment. Our analysis showed that the scale of disruption is not quantitatively dissimilar to that which Autor identified over the past thirty years. For more information on that aspect of our analysis, please refer to Annex 3. In general, the picture is mixed. There will be net-negative and net-positive effects across the breadth of the skills spectrum. The way each worker is affected will depend on her specific balance of skills and how well she will adapt to the changing needs of the labor market.

Our labor market forecast reveals the pressure points and the growth areas implied by our 2027 technology landscape. A representation of our granular results is displayed in Box 4 and Box 5. These industry-occupation matrices drill down into the results of Fig. 16 and Fig. 18 in more detail. They reveal how the pressure being felt by the government services and transport industries, for example, is distributed across different occupations in those industries, or how the job losses in office and administration jobs, for example, are distributed across sectors of the economy. With this insight into the main pressure points of the 2027 labor market, we can see which occupations are on the rise and which are in decline. However, who will fill vacancies in the former, and what will the latter go on to do?

5.3 MAKING THE TRANSITION TO THE 2027 LABOR MARKET

We developed the Oxford Economics Skills Matching Model to simulate the dynamics of the labor market and explore how its many participants will react to this disruption. If the 2027 labor market changes shape in the way our scenario suggests, who will fill the vacancies that arise? How will redundant workers reapply themselves to new opportunities? Our sophisticated labor market model addresses this question empirically for the first time. The model combines two crucial data sources to measure how compatible jobs are with each other. This is key to predicting where a displaced worker may go if she loses her job, or who an employer might seek out to fill a vacancy. U.S. longitudinal household surveys provide decades worth of real world evidence of the job moves individuals have made in the past. The O*NET database provides quantifiable data on the skills, knowledge and experience required in each occupation, which enables us to assess their theoretical compatibility.

We use these rich datasets to construct a probability model, combining an interdependent sequence of over 15,000 probability matrices. These matrices contain information about the likely route to employment that any worker would take if displaced from his or her job. It matches worker preferences with employer vacancies in the labor market to find a new equilibrium. For example, if a vehicle operator is displaced from her job in the manufacturing industry, historical precedent and the worker's characteristics dictate that she is more likely to find new employment within the manufacturing industry than elsewhere. This is because she will seek a job that makes the most of her existing skillset, knowledge and experience – as that is the job which will be most financially rewarding. We developed an algorithm to map the moves that workers in over 800 occupations in the U.S. labor market would make, across 19 industries of the economy, to build a highly-detailed matching model. We also imposed a set of conditions on our model to ensure it captured the fundamental dynamics of the labor market. These are set out below.

Box 4. Net Change in Employment Across the U.S. Labor Market by 2027, Total Net Flows

Disruption hot spots: Below is an industry-occupation matrix representation of the U.S. labor market. It reveals the clear divisions that emerge in our 2027 technology scenario. Green cells represent those sections of the market needing more workers and red cells those sections that will be reducing their workforce. The government and (other) services sector (which includes repair and maintenance, personal services, like laundry or pet-care, and community services, such as religious organizations) will be amongst the largest source of displaced workers in this time period. Also, the transport and material moving occupational group, consisting mostly of drivers, will be one of the key pressure points. Large numbers of workers from this group will find their skills redundant and will need to retrain to remain relevant in an evolved labor market. The manufacturing industry is facing a major disruption. We forecast net losses for half the occupational groups in this industry, in particular low-skilled production occupations, maintenance and repair jobs, and drivers. Within the industry, meanwhile, we expect net gains for management, designers and computer experts to occur in parallel.

Change in employment by industry-occupation matrix, 2017-2027

	Agri-culture, Forestry, Fishing and Hunting	Mining	Utilities	Con-struction	Manufac-turing	Wholesale Trade	Retail Trade	Transpor-tation and Warehous-ing	Information	Finance and Insur-ance	Real Estate and Rental and Leasing	Profession-al, Scien-tific, and Technical Services	Office and Admin-istrative Support	Educational Services	Health Care and Social Assis-tance	Arts, Enter-tainment, and Recre-ation	Accom-modation and Food Services	Other Ser-vices (inc. personal/ laundry services)	Federal, State, and Local Gov-ernment
Management	200	-1,100	-2,400	27,900	15,500	26,700	19,000	1,300	18,300	34,900	11,400	54,400	64,100	900	61,200	4,100	-16,200	-21,200	-20,400
Business and Financial Operations	-100	-2,100	-3,400	9,100	-3,400	4,800	800	-1,500	9,800	34,800	-800	38,400	40,900	-3,100	17,000	1,300	-1,600	-25,900	-74,500
Computer and Mathematical	-	-400	-1,400	500	4,100	6,900	900	-400	37,900	14,200	300	83,300	27,500	200	6,900	100	-100	-4,000	-16,800
Architecture and Engineering	-	-2,300	-4,900	600	-33,700	-	-100	-900	2,100	-	-100	2,800	2,300	-500	200	-	-	-1,100	-27,100
Life, Physical and Social Science	-100	-1,300	-1,500	-	-9,100	-400	-	-100	100	100	-	3,000	-400	-5,100	4,300	-	-	-1,300	-28,100
Community and Social Services	-	-	-	-	-	100	-	-	-	200	-	400	1,500	6,500	50,200	-	-	-10,600	-28,100
Legal	-	-400	-100	100	300	200	-	-	700	500	-200	29,900	3,200	100	400	-	-	-600	-11,800
Education, Training and Library	-	-	-	-	-	-	-	-	700	-	-	500	2,800	1,600	24,600	100	-	-6,500	-10,900
Arts, Design, Entertainment, Sports and Media	-	-	-100	400	100	1,600	800	-	20,000	800	500	14,200	4,100	10,900	2,300	9,700	-500	-6,100	-2,600
Healthcare Practitioners and Technical	-	-500	-300	-	-1,000	200	5,100	-300	-	-300	100	-300	1,300	-6,800	171,500	200	-	-1,200	-34,900
Healthcare Support	-	-	-	-	-	-	2,400	-	-	100	-	6,800	7,000	700	269,900	100	-	-3,300	-2,600
Protective Service	-	-100	-800	-100	-1,000	-200	-2,400	-1,000	-100	-300	-1,300	-400	-14,200	-5,700	-700	-400	-5,900	-3,700	-180,800
Food Preparation and Serving Related	-	-	-	-	2,400	400	36,100	200	4,300	-	1,300	500	8,700	24,300	56,000	24,400	367,000	-3,800	200
Building and Grounds Cleaning and Maintenance	100	-	-100	2,900	2,900	1,500	7,900	1,300	700	700	10,000	2,500	160,400	19,600	43,900	12,000	18,200	-5,800	-4,000
Personal Care and Service	200	-	-	-	100	100	2,300	1,100	4,500	-	1,000	2,900	5,300	11,000	114,700	31,300	2,800	-67,500	-1,500
Sales and Related	-	-500	-600	9,100	4,300	49,400	666,500	500	26,800	67,100	6,300	22,400	43,000	1,700	7,100	10,600	14,700	-19,300	-100
Administrative and Support and Waste Management and Remediation Services	-1,100	-6,000	-9,300	-4,900	-56,200	-10,500	79,800	-135,800	11,500	66,200	-9,200	-19,100	43,700	-50,500	43,900	-2,700	-300	-75,600	-157,900
Farming, Fishing and Forestry	-24,800	-	-200	-100	-2,300	-2,800	-1,200	-300	-	-	-	-300	-500	-200	-	-	-	-200	-3,500
Construction and Extraction	-	-47,300	-3,500	-4,300	-10,600	-800	-2,500	-1,700	200	-	-700	-	2,100	-1,800	200	-300	-300	-1,800	-56,100
Installation, Maintenance and Repair	-600	-8,200	-14,700	1,500	-49,100	-14,200	-23,800	-15,400	1,700	-500	-21,600	-1,700	-5,200	-10,900	-3,000	-4,200	-12,100	-112,200	-47,400
Production	-1,800	-6,700	-14,100	-7,200	-551,200	-20,800	-11,800	-6,800	-300	-	-	-4,900	-39,600	-500	3,300	-	600	-36,300	-17,300
Transportation and Material Moving	-2,400	-15,800	-1,800	-11,900	-99,000	-102,300	-76,000	-368,000	-2,900	-200	-11,300	-7,000	-93,100	-35,900	-300	-4,900	-27,700	-66,900	-53,000
Total	-30,400	-92,700	-59,200	23,600	-786,900	-60,100	703,800	-527,800	136,000	218,300	-14,300	228,300	264,900	-43,500	873,600	81,400	338,600	-474,900	-779,200

Box 5. Net Change in Employment Across the U.S. Labor Market by 2027, Focused on Biggest Employers

Major markets: From a strategic perspective, policymakers, business leaders and educators may be interested in prioritizing the major sources of pressure on the labor market. The U.S. industry-occupation matrix is reproduced below but highlighting only the biggest employing parts of the labor force (i.e. those constituting 70 percent of jobs). Again, the government and other services sectors displace some of the largest numbers of workers. Our results also suggest policymakers might do well to prioritize policies that ease the transition process for workers in transport jobs. Office and administrative workers appear to be displaced from some large industries, but presented with opportunities in others. The green cells in the management occupations and professional services industry mean these parts of the labor market will be the biggest net creators of jobs and will face the most significant recruitment challenge.

Change in employment by industry-occupation matrix, 2017-2027: Major employers

	Agri-culture, Forestry, Fishing and Hunting	Mining	Utili-ties	Con-struc-tion	Man-ufac-turing	Whole-sale Trade	Retail Trade	Trans-portation and Ware-housing	Infor-ma-tion	Fi-nance and Insur-ance	Real Estate and Rental and Leas-ing	Pro-fes-sional, Sci-entific, and Tech-nical Ser-vices	Office and Admin-istrative Support	Ed-uca-tional Ser-vices	Health Care and Social Assis-tance	Arts, Enter-tain-ment, and Rec-re-ation	Ac-com-mo-dation and Food Ser-vices	Other Ser-vices (inc. per-sonal/laun-dry ser-vices)	Fed-eral, State, and Local Gov-ern-ment
Management					2%							7%	8%		9%				
Business and Financial Op-erations										2%		3%	5%						-7%
Computer and Mathematical												6%							
Architecture and Engineering					-4%							0%							
Life, Physical and Social Science																			
Community and Social Services															5%				
Legal												4%							
Education, Training and Library														0%					
Arts, Design, Entertainment, Sports and Media																			
Healthcare Practitioners and Technical															3%				
Healthcare Support															8%				
Protective Service													-2%						-9%
Food Preparation and Serving Related																	5%		
Building and Grounds Cleaning and Maintenance													9%						
Personal Care and Service															7%			-10%	
Sales and Related						3%	9%			8%									
Administrative and Support and Waste Management and Remedi-ation Services					-5%	-1%	3%	-10%		3%		-1%	2%	-4%	2%				-10%
Farming, Fishing and Forestry																			
Construction and Extraction				0%															
Installation, Maintenance and Repair							-3%											-16%	
Production					-9%								-5%						
Transportation and Material Moving					-10%	-9%	-8%	-11%					-8%						

5.3.1 GENERAL VS SPECIFIC SKILLS

Workers with different skillsets or career specializations face different career paths, and this can affect the calculation they make when considering job moves. In his seminal 1964 paper, Nobel prize winning economist Gary Becker distinguished between two types of skills in the workforce: general and specific.[12] General skills are those that are transferable and might be usefully applied across functions, companies and industries. Specific skills refer to those skills that are tailored to a specific field, industry or even company. This distinction is very important to labor market dynamics. Specific skills are often more valuable to companies and better paid, perhaps reflecting many years of experience and training. They might include highly specialized mechanical engineers, experts in a particular branch of law or managers with well-established networks in and detailed knowledge of a particular industry. Workers with high levels of specific skills are less likely to move jobs laterally across industries, and would be unlikely to command the same wage, because their specializations are of little use outside their own niche sector. The moves they would typically make are up or, less likely, down the hierarchy in the same field.

Workers with strengths in general skills tend to have greater freedom to roam. Unlike specific skills, general skills have the advantage of being widely applicable, but they are less well paid as a result. Our model reflects these dynamics, by drawing on real historical data about the job moves people have made throughout their careers.

5.3.2 WAGE PRESSURES

In the real world, workers consider their job moves based not only on their ability to do the job, but also the wage that it commands. The relative wage levels between occupations form part of the calculation of probability matrices, to the extent that they are reflected in historical job moves. Our model enables us to capture the impact of the 2027 technology scenario on those relative wage expectations of different occupations, which will influence the job moves people make. For example, a vacancy for a home health aide in our scenario could recruit from a pool of occupations with compatible skills and wage expectations. A postal worker, with a bit of training, could be a viable candidate for the job, as could a childcare assistant. But the 2027 scenario shows how the postal worker profession is shedding large numbers of workers due to automation, while childcare workers are in great demand. Therefore, the surplus postal workers will most likely have lower wage demands than the scarce childcare assistants, and will therefore be more competitive in bidding for the health aide job. Because the model solves iteratively, these wage pressures evolve with labor market conditions. To fill the first vacancies, the postal workers' low wage expectations will work in their favor. But as the surplus of postal workers reduces, their wage demands may grow and their competitiveness for the last health aide positions may fall.

12 Becker G., (1964) "(1984) "Human Capital" 2nd edition. Columbia University Press, New York.

5.3.3 CASCADING CHANGE

The model does not simply fill the vacancies with the redundant workers. Instead it simulates how job vacancies cascade through the labor market. Sometimes displaced workers have skills that are simply not compatible with those required in a vacant job. Nothing in the historical labor market evidence or occupational profiles suggest that such a move could be made. But it does not mean that displaced worker will be be stranded without a job. Vacancies tend to ripple across the labor market until it finds a new equilibrium. A managerial vacancy in real estate, for example, would not be filled by a displaced maintenance worker from the manufacturing industry. But as the managerial vacancy attracts interest from qualified applicants, they leave vacancies in their own wake, which are filled by others. There are around 4.3 million workers displaced from their jobs under our 2027 technology scenario. Because of the cascading effect, displacing 4.3 million workers actually leads to almost 6.5 million total job moves to re-establish equilibrium.

This highly data-intensive modeling provides us unique insights into how today's labor market must evolve in response to our 2027 technology landscape. We estimate the moves workers will make across the labor market to respond to the shift in demand. How productive the economy is depends on how smoothly the transition proceeds and how well prepared the workers are to meet the requirements of their new roles. The U.S. economy faces a significant reskilling challenge. In the next chapter, we explore what this challenge entails.

Chapter 6

The Implications for Skills

The Skills Matching Model illustrates how the labor market will evolve around advances in technology over the next decade. Opportunities will grow in some industries and shrink in others. Workers will find some of their marketable skills rendered obsolete, while the demand for others rises. In order to meet the needs of that 2027 economy, workers will have to adapt to new realities, retrain and seek out new openings. This means that in the future, individuals from all backgrounds will increasingly be expected to work with and understand technology in order to do the jobs that never previously required it.

To prepare and equip the workforce for the demands of the 2027 economy, policymakers, business leaders and educators need to know where the skills shortfalls will be and how to focus their reskilling efforts to smooth the transition. In this chapter, we use the Skills Matching Model to identify the displaced workers and trace the moves they will make to new employment. We contrast the skills requirements of their original occupation with that of their new occupation in 2027, and assess the skills they will have to acquire to meet the demands of their new job. This gives us unprecedented insight into the reskilling challenge facing the U.S. workforce. We start by taking a high-level look at what skills will be in short supply before focusing on the acute skills shortfalls relating to ICT jobs. We then draw out the key story emerging from our analysis – the growing need for “human skills” over the next decade that must be addressed to prepare the workforce to make the most of the digital revolution.

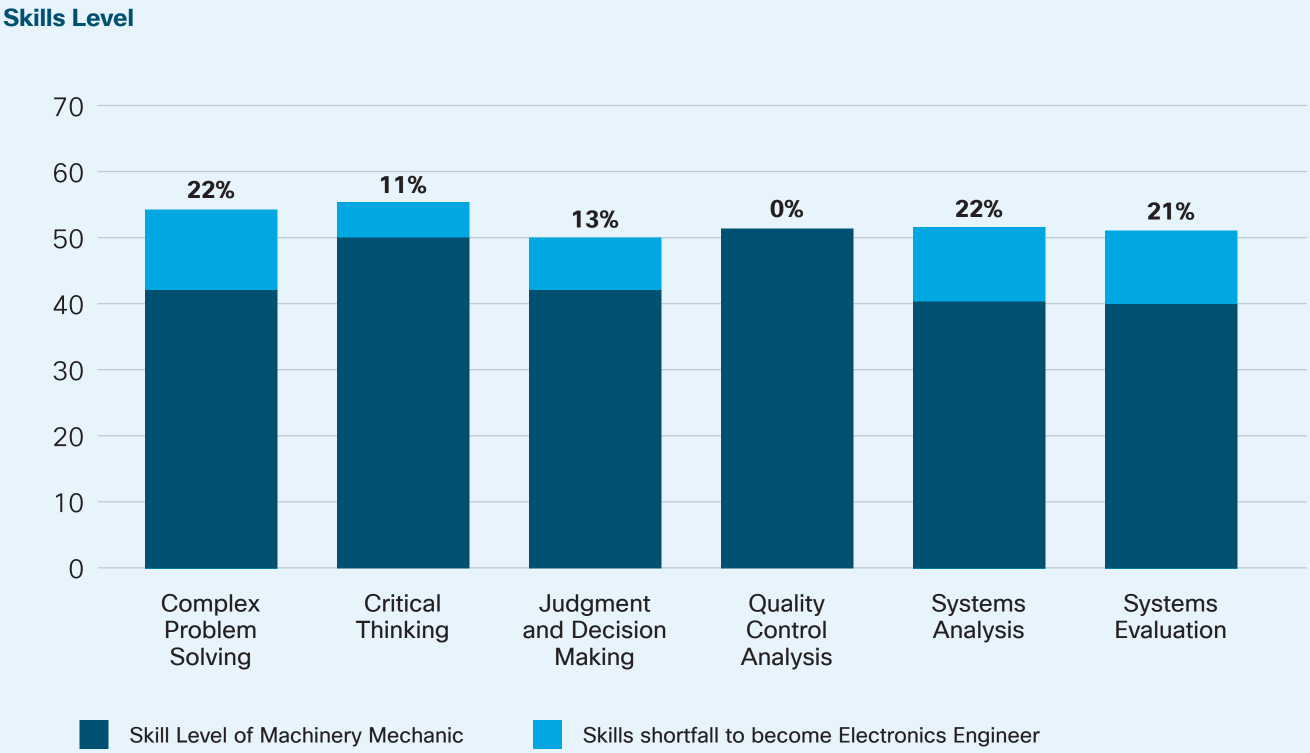
6.1 MEASURING THE SKILLS SHORTFALL

We characterize the skills shortfall facing the U.S. labor market by contrasting the skills demanded in the 2027 labor market with the skills available today. As the foundation of our estimate, we quantified the skills profile for every one of over 800 occupations using the O*NET database. Again, for more details on the O*NET database and how we use it, refer to Annex 4. We trace every single move that is made to take the labor market back to equilibrium in 2027 and aggregate the skills shortfalls that emerge.

Box 6. What Skills Shortfall Would a Machinery Mechanic Face to Become an Electronics Engineer?

To illustrate how skills shortfalls are estimated, we present an example of a common job move in our model: a machinery mechanic to an electronic engineer. The mechanic is sufficiently qualified for the engineering job in some elements of her skills profile, but would face a significant learning curve in others, including systems evaluation, critical thinking, complex problem solving and systems analysis. In order to estimate the size of this skills shortfall, we quantify the skills profile of both occupations using O*NET data and calculate the machinery mechanic's "skills points" as a share of those required to be an electronics engineer.

A machinery mechanic moving to an electronic engineer job: Skills shortfall



Source: Oxford Economics

6.2 ACUTE-SKILLS SHORTFALLS FACING THE U.S. ECONOMY

Technology-related jobs present the most acute skills shortfalls. By estimating the reskilling challenge of each of the 6.5 million workers that move jobs in our scenario, we can build, from the bottom up, a rich picture of the strategic challenges facing the 2027 labor market. Breaking down the skills shortfall by type of skill reveals that technology-related skills present the steepest learning curves. Fig. 20 lists the top-ranking skills shortfalls, by skill type, and shows that the top three skills shortages relate to technology or equipment skills: namely installation (of equipment, machines, programs etc.), programming and technology design. The most acute skills shortfalls also include operations analysis, equipment maintenance and science skills. This means that workers likely to move into programming-related jobs in the next 10 years, for example, are 59 percent short of where they need to be and will need training.

Fig. 20 Top 10 skills shortfalls by skill-type

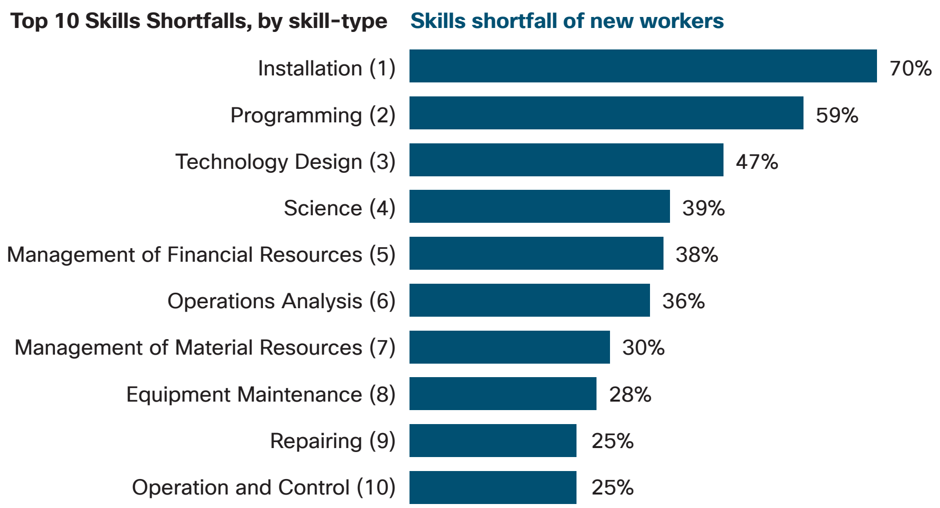


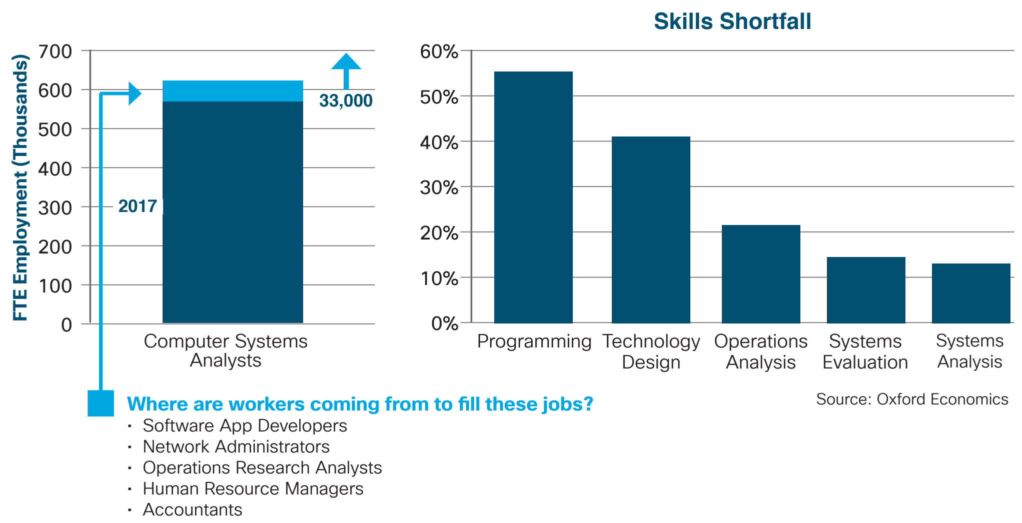
Fig. 21 Skills defining the ICT skills shortfall

Information and Communications Technology (ICT) Skills

Technology Design	Basic Programming	Advanced Programming
Generating or adapting equipment and technology to serve user needs.	Writing computer programs (e.g. coding in a programming language to analyze data).	Writing computer programs (e.g. software development).
Systems Evaluation	**System Analysis**	**Operations Analysis**
Identifying measures of system performance and the actions needed to improve performance based on system goals.	Determining how a system should work and adapt to changes in operations and the environment.	Analyzing needs and product requirements to create a design.

To better understand the Information and Communications Technology (ICT) reskilling challenge, we focused our analysis on a carefully selected suite of ICT skills. Lifted from the O*NET typology, these include technical skills such as programming, as well as other "softer" skills that are important to ICT jobs. We identified these softer skills by analyzing the skills profiles of current ICT professionals in the O*NET database. We looked for frequently appearing "other skills" in ICT professions, the types of skills that revealed themselves as complementary to performing skilled ICT tasks. They are defined by O*NET as operations analysis, systems analysis, systems evaluation and technology design, as detailed in Fig. 21.

Fig. 22 Acute skills shortfall in Computer Systems Analysts (Left: Percentage change in full time equivalent (FTE) employment (thousands), Right: Absolute change in FTE employment (%))

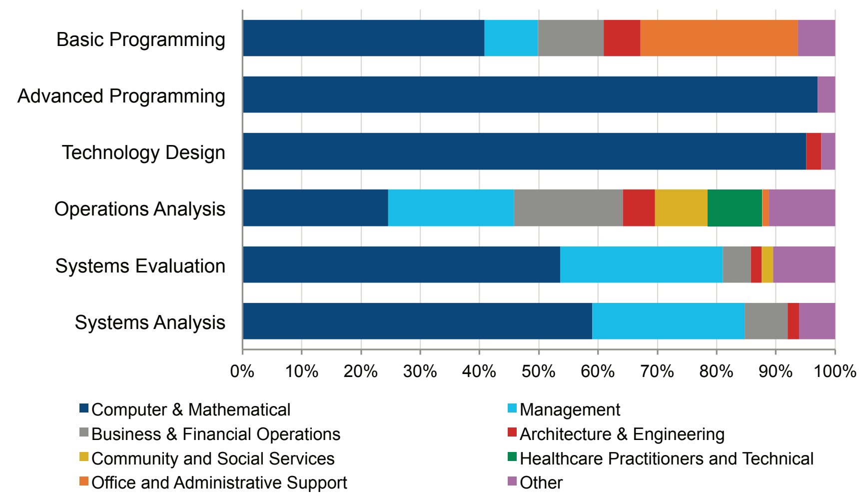


Source: Oxford Economics

The reason the skills shortfall in technology areas is so severe, is that technology jobs require high levels of specialist skills that are rare in today's labor market. The demand for computer systems analysts, for example, is forecast to grow by around six percent over the next decade as a result of our scenario. As illustrated in Fig. 22., this job requires a high degree of programming, systems analysis, systems evaluation and technology design skills, but many of the workers that are most likely to fill the vacancies are presently underqualified. According to the Oxford Economics Skills Matching Model, they include data administrators and software app developers, but also human resource managers and accountants who do not currently exhibit the skills required for their future roles. The skills shortfall suggests the workers most likely to fill those vacancies will have less than half of the required programming skills. They will also fall 40 percent short of the required technology design skills, and approximately 15 percent short of the required systems evaluation and systems analysis skills.

The technology skills shortfall is not exclusive to ICT specialists. Workers from across the economy will be needed to work with and service the technology infrastructure upon which they are increasingly dependent. Our 2027 technology landscape describes a world where workers at all levels will be guided by artificial intelligence and will be expected to interact with computers daily. In industries where ICT skills have traditionally been irrelevant, they will become business-critical; for example, in healthcare, utilities, logistics and retail. And this transformation will rise up the hierarchy as managers consult AI applications to perform tasks ranging from basic schedule management to considering a series of complex options. Achieving this transition, will require a vast expansion of ICT skills.

Fig. 23 Information and Communications Technology (ICT) skills gap by occupational group and ICT skills component



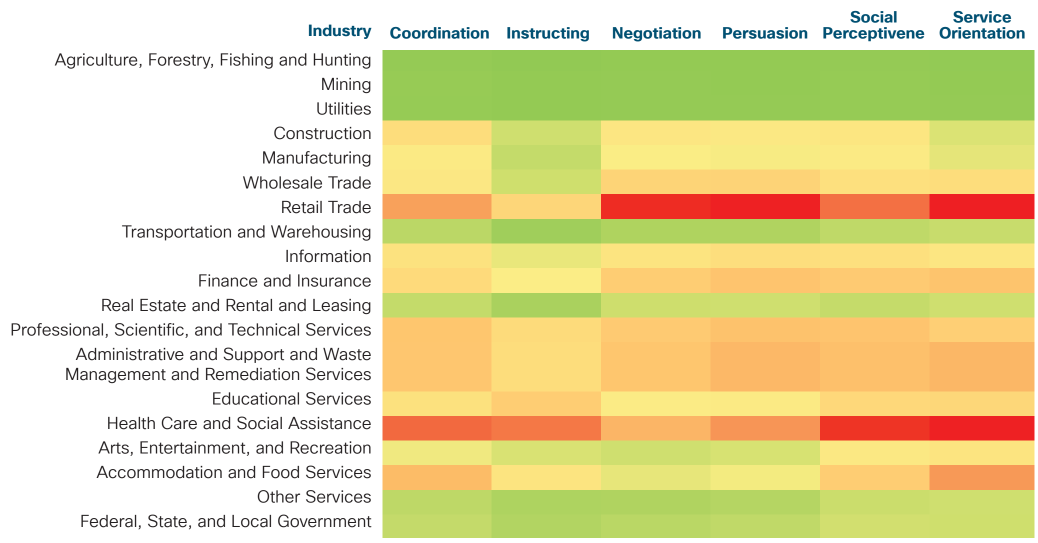
Source: Oxford Economics

We found that the ICT skills required for the 2027 labor market are multi-faceted and broadly spread. While the ICT skills shortfalls occur mainly in computing and mathematics professions, which include software developers and data scientists, a large share of the ICT skills of the future will be demanded outside this occupational group. In particular, for more basic programming skills, systems analysis and systems evaluation, we see substantial skills shortfalls in managerial positions, business, and finance professions. The ICT skills shortfalls even extend, although to a lesser degree, to workers in the construction, manufacturing, arts and healthcare industries.

6.3 BROADER RESKILLING CHALLENGES FACING THE WIDER WORKFORCE

Paradoxically, as technology becomes more powerful and capable, it is the rise in demand for "human skills" that marks the transition to the 2027 labor market. Workers whose core purposes are critical and creative thinking and making human connections will thrive. These workers will define themselves by their ability to use and work creatively with technology rather than compete against it. Stepping back from the acute skills shortages we will see in technology jobs, it is the development of these "human skills" that constitutes the greatest reskilling challenge, from an economy-wide perspective. Our 2027 employment forecast suggests that human skills—such as coordination, instruction, negotiation, and persuasion—are complementary to technological innovation, apply to a large range of jobs and are crucial to rebalancing the labor market. In fact, 32% of the total skills gap facing the U.S. economy by 2027 is in "human skills".

Fig. 24 "Human skills" gap heat map, by industry (Cells are colored relative to one another, with red cells revealing industries with the largest "human skills" gap and green cells the smallest.)



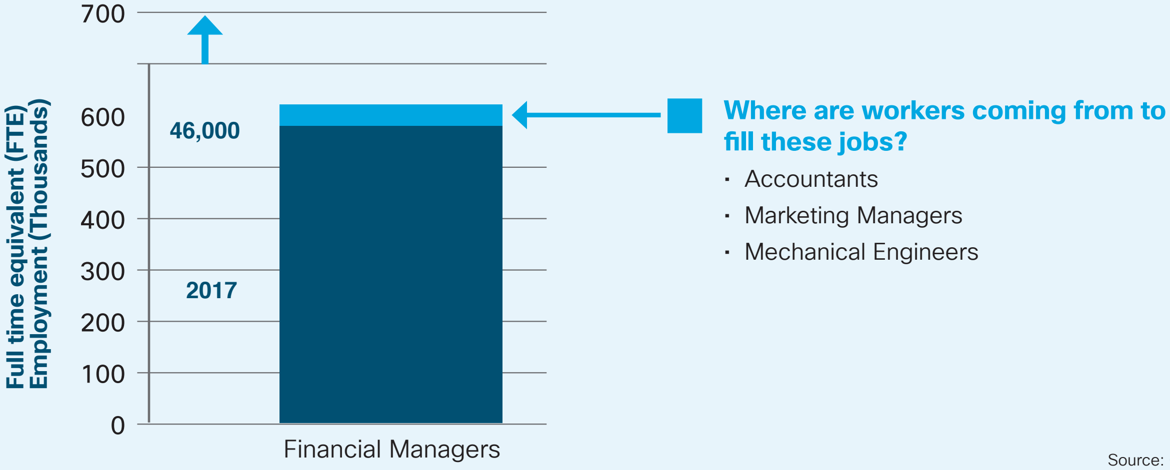
The continuing migration of jobs to the services industries under our 2027 employment forecast exposes a significant gap. This is highlighted in the heat map in Fig. 24, which shows the severity (red) of the skills shortfall for six key soft skill types across industries. In the retail industry, where negotiation, persuasion and service orientation are highly valued, the workers moving into vacancies in these industries will need to reskill and adapt. Considerable social skills gaps emerge also in healthcare and administrative support sectors, as workers adapt their skillsets around new technology and work with machines to better exploit their comparative advantages.

These are the skills that will define the success of the U.S. labor market of the future because they embody the economy's ability to make the best use of technological innovations on a large scale. Policymakers, business leaders and educators are challenged with managing a smooth transition. That will mean equipping those in jobs and those displaced by new technologies with the skills that will matter most in the decade ahead.

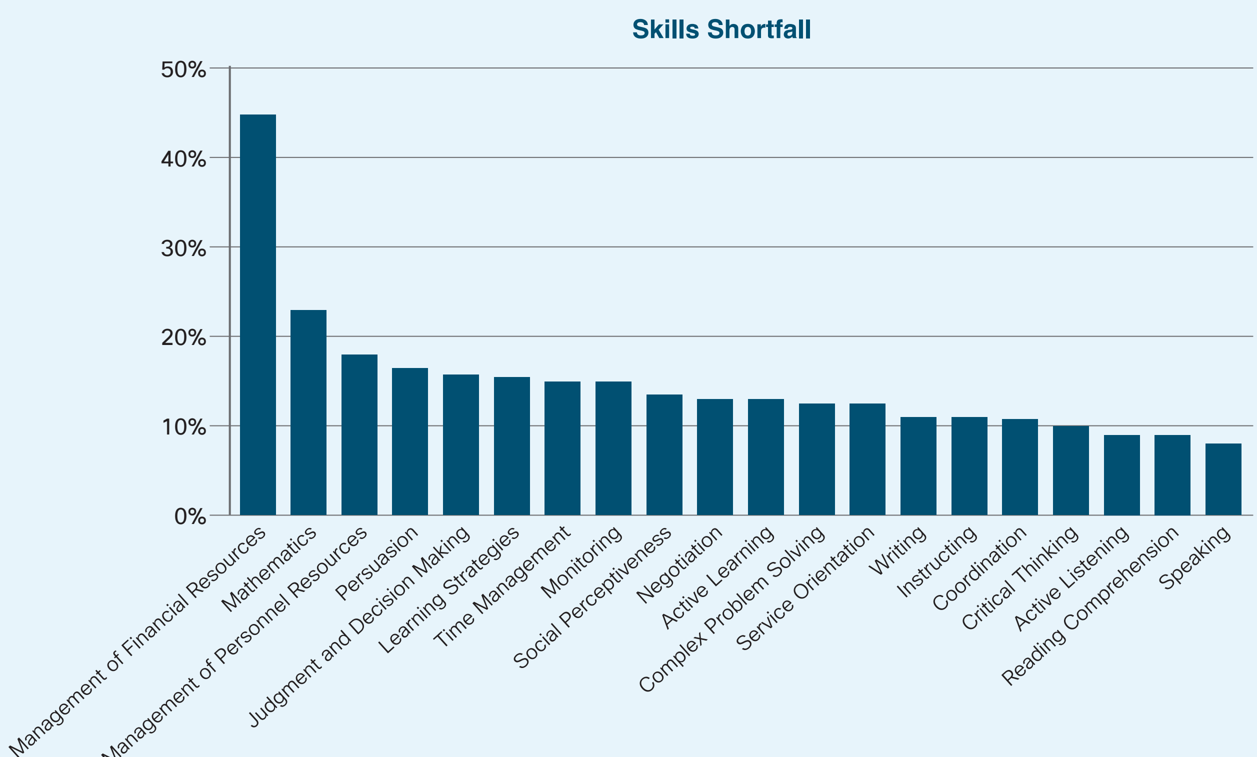
Box 7a. How we calculate the skills shortfall? A Spotlight on the Skills Shortfall for Financial Managers

Over the next 10 years, we forecast the number of Financial Managers in the U.S. economy to grow by more than 46,000. Those positions are filled by a variety of applicants, including Accountants and Advertising Managers. Many of those new entrants do not have the skills required to do the job, and we can measure the size of the skills gaps on all 20 skills deemed important to being a Financial Manager. As shown below, the key skills gaps relate to Management of Financial Resources and Mathematics.

Skills shortfall facing new Financial Managers



Source: Oxford Economics

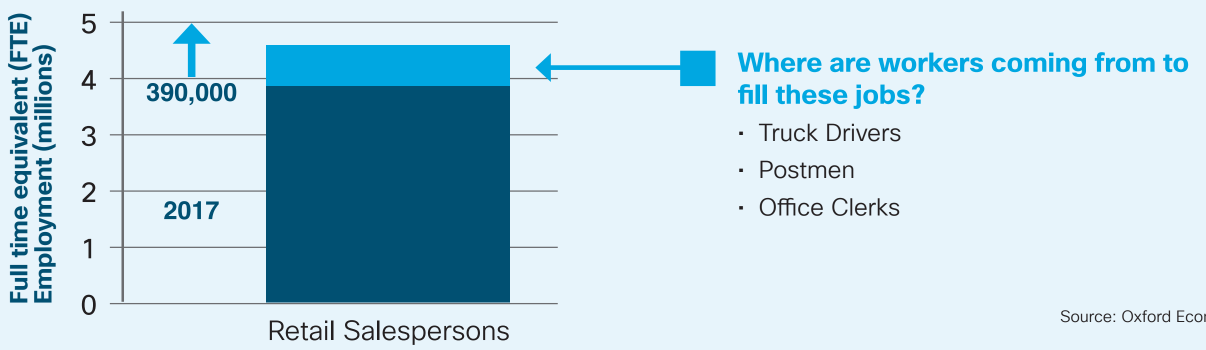


Source: Oxford Economics

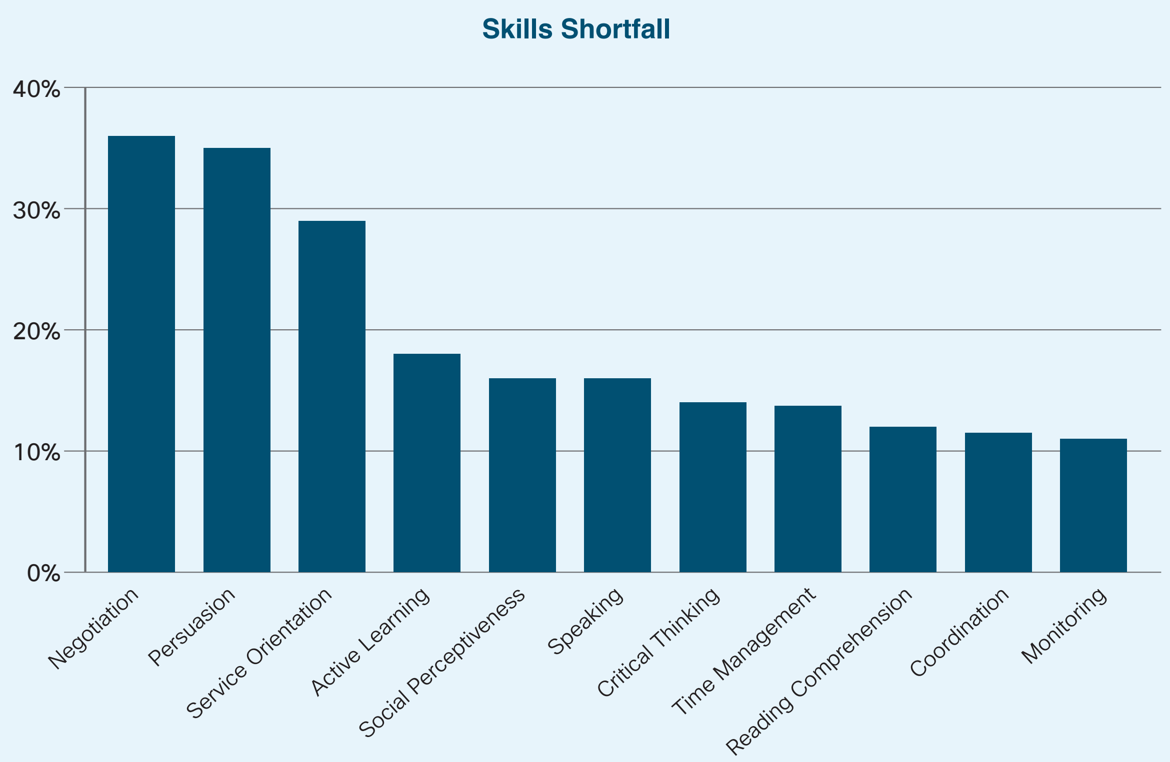
Box 7b. How we calculate the skills shortfall? A Spotlight on the Skills Shortfall for Retail Salespeople

An additional 390,000 Retail Salespeople will be required by 2027. Truck drivers, Postal workers and Office Clerks are among those that will fill the vacancies, but they will face important skills gaps. There are three key skills shortfalls that stand out: negotiation, persuasion and service orientation.

Skills shortfall facing new Retail Salespeople



Source: Oxford Economics

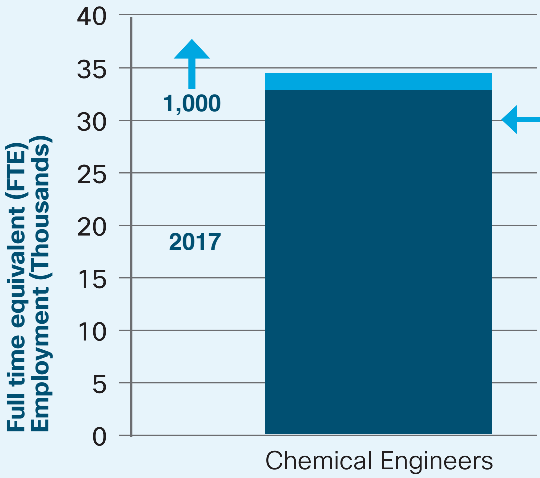


Source: Oxford Economics

Box 7c. How we calculate the skills shortfall? A Spotlight on the Skills Gap for Chemical Engineers

Information and Communications Technology (ICT) skills gaps are not confined to ICT occupations; take Chemical Engineers as an example. To fill 1,000 vacancies by 2027, they will draw from occupations such as Geoscientists and Mechanical Engineers. The incoming workers may match many of the skills required for chemical engineering, but many face skills gaps in operations analysis, programming, systems evaluation and systems analysis

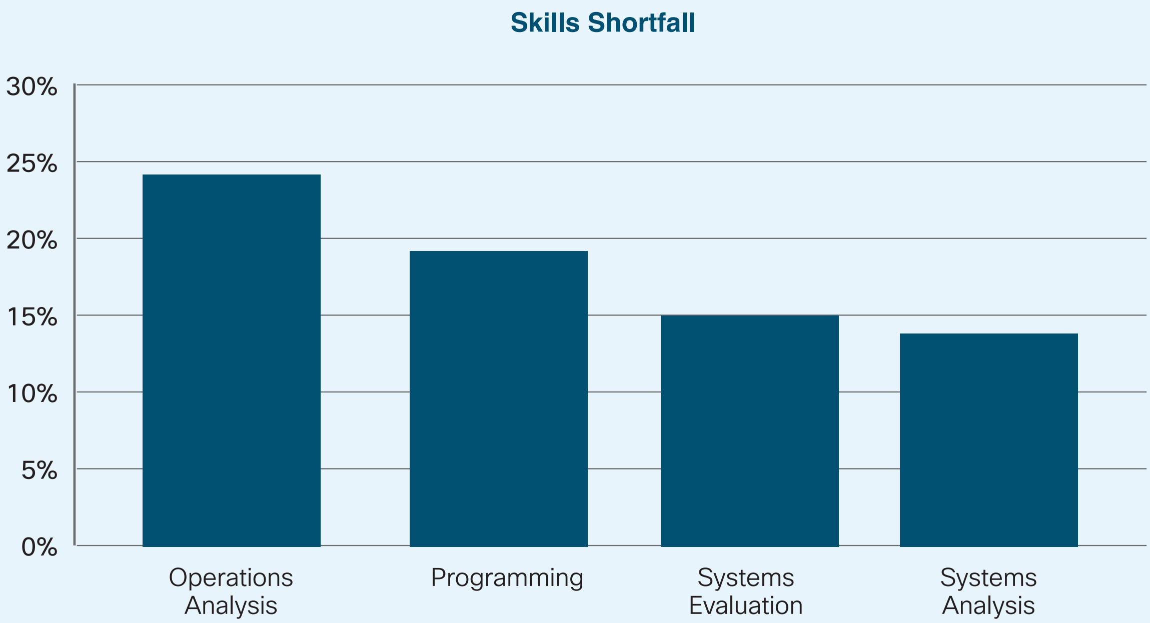
ICT skills shortfall facing new Chemical Engineers



Where are workers coming from to fill these jobs?

- Mechanical Engineers
- Geoscientists
- Nuclear Engineers

Source: Oxford Economics



Source: Oxford Economics

Chapter 7

Conclusion

Over the course of the next decade, all workers will feel the impact of technology in their working lives. The scope of digital disruption will be wider than ever, crossing industry lines and touching businesses of all shapes and sizes. Some workers, such as truck drivers and postal workers, will see many of the functions they are paid to perform today competed away by technology. They will need to adapt and retrain if they are to remain relevant in the future workplace. There is a human cost to this displacement in the short term, which we cannot ignore. Displaced workers may suffer periods of uncertainty and falling living standards, at least in the short term. Other workers, meanwhile, will find the functions they perform enhanced or augmented by technology, and will see new opportunities arise as a result. Over the course of time, abstracting away from the personal challenges individuals will face in periods of disruption, the labor market will evolve and adapt to the demands of the new economy.

How smoothly today's labor market makes the transition to the demands of the future is of crucial importance. The less prepared that workers are for the shift, the more painful the disruption will be. This study paints a picture of where automation will hit workers hardest in the U.S. economy and where the alternative employment opportunities will arise. It highlights which skills of tomorrow are most lacking today, and which sectors of the economy have the greatest need for them. In doing so, it provides a unique platform for policymakers, business leaders and educators in the U.S. labor market to embrace the complexities of the labor market's relationship with technology, in order to meet the great reskilling challenges of the next decade.

At the highest level, the story of the next 10 years is in keeping with the broad sweep of labor market history. Technology will improve our ability to conduct a growing range of workplace tasks. In many respects, workers will come under increasing competition from technology. More often than not, they will be complemented by it. Ultimately, humans will continue to utilize the tools at their disposal to push the boundaries of what they are capable of, and to prosper by doing what humans do best.

ANNEX 1

THE 2027 TECHNOLOGY LANDSCAPE

In order to explore the labor market impacts of technological change, we needed a consistent and balanced scenario upon which to base our assumptions. We developed a high-level 10-year technology landscape to serve this purpose. The landscape was based on extensive literature review and consultation with technology experts and thought leaders in Cisco and Oxford Economics. We used sophisticated scenario development techniques to form a comprehensive vision of how technological advances might roll out across the U.S. economy over the next 10 years. A systematic approach was used, building the scenario around three pillars of change: the generation of data, the computing power to make sense of that data, and the ability of industry to match those technical advances with the equipment and applications that will make use of it.

This exercise was not about predicting the possible political and social changes that might interact with the technology landscape over the coming years. We therefore assumed that the decade to 2027 would be characterized by an enabling environment that is supportive of technological progress, unmarked by any major disruptions to energy prices or materials supply, or by catastrophic climate or socio-political developments. In energy, for example, we assumed prices would be stable; consumption would not yet have peaked but natural gas and renewables would be absorbing the marginal increases.

We also assumed a positive, but benign macroeconomic context: U.S. GDP would grow at a steady rate of two percent per annum over the decade, with investment growth of 3.5 percent per annum and no major financial crises. The U.S. population would continue to grow at a rate of 0.75 percent per annum but get steadily older, with the number of people over the age of 64 increasing from 15 percent to 19 percent of the total by 2027.

Below we set out the 2027 technology landscape, which laid the platform for developing our modeling assumptions.

Mobile technologies and the Internet of Things mean everything is connected
By 2027, the Internet of Things and mobile technologies are deeply embedded in everyday life in both the personal and business spheres. The average U.S. citizen connects with more than 15 smart devices in the course of the day—her phone, car, fridge, heating, clothes etc. all encompass digital technologies. In business, too, smart, networked devices conduct many of the tasks traditionally undertaken by employees—cheaply, efficiently and invisibly.

For consumer-facing-companies, this level of connectivity provides real-time intelligence on consumer habits and preferences and puts unlimited information in the hands of consumers, to make well-informed decisions. Companies compete to "know most" about their customers and there are great rewards for those that successfully target the most bespoke offers and wrap-around customer care. Digital services and mobile apps cater for every aspect of living in a highly-personalized way, from PH-rebalancing breakfast recommendations to voice-activated household chores when you are stuck in traffic on the way home.

In industry, supply chains and production lines use smart, networked sensors to maximize productivity gains—establishing almost flawless product tracking and quality control mechanisms. Networked robots have long since surpassed the price and efficiency of workers in performing low-skilled, routine functions such as machine maintenance or security surveillance. Advances in wearable technologies and smart machines are also vastly improving the health and safety of workers – from agriculture, to mining, to manufacturing –robots are able to cheaply identify risks and take on the more dangerous tasks.

Within companies, mobile working is commonplace: 50 percent of workers spend at least one day per week on location or outside the office. Indeed, there are few jobs that cannot be conducted remotely and according to a flexible timeframe, thanks in large part to advances in collaborative technologies and a widespread cultural acceptance of the merits of mobile working. Nonetheless, the majority of companies still value "in-person" contact and collaboration, so the centralized office or workplace remains important.

More than 60 percent of the world's data is now held in the cloud and cloud services dominate the provision of many business functions. Many companies no longer operate IT services or Human Resources in house, for example, choosing to out-source such functions from cloud providers. For many companies, this extends to training delivery too, with bespoke, flexible, real-time learning and development services delivered via mobile technologies to staff across enterprises and industries.

Leaps forward in artificial intelligence and data analytics have changed the nature of work

From product and service design to strategy development and business planning, companies place a heavy emphasis on analytics. Thanks to real-time and predictive analytics capabilities, workers at all levels are guided by data. At one end of the spectrum, Chief Executives use predictive analytics to help them determine the most effective path through the potential pitfalls of a merger agreement, at the other, contract cleaners depend on real-time analytics to optimize their cleaning route around the hotel.

Artificial Intelligence is commonly used to augment decision making. Managers consult AI throughout the day from scheduling client meetings to ensure full attendance, to delegating tasks to maximize a project team's talents, or even weighing up the options to deal with operational failure or underperforming employees. In many industries, AI draws on vast meta-data to provide managers with a forensic analysis of the behavioral patterns and performance of their workers. As a result, Human Resources practitioners and managers interact consistently with technology to build teams, measure performance and manage change.

Routine cognitive activities that were once the core of certain white collar professional reputations have been automated by software bots, such that professionals have begun to define themselves by the value they can add to bots, rather than competing directly against them. An accountant who may have traditionally been valued for her conscientiousness and stock of knowledge to ensure statutory compliance within a company's books, is now valued for her problem-solving and communication skills as she works with clients to overcome the non-compliance issues the software has efficiently discovered.

Indeed, most occupations are evolving to meet advancements in technology. Almost all jobs require at least a basic level of interaction with computers. In some industries where ICT skills had traditionally been irrelevant, they are now business critical; for example, in healthcare, utilities, logistics and retail.

Hyper-fast internet has been rolled out across the U.S., reaching more than 50 percent of homes and providing instantaneous access to the internet. Rapid advances in distributed computing systems mean computing power continues to accelerate at pace by spreading the computational burden over a larger network. Battery capacity has doubled since 2016, as it did in the decade before. This has lowered the cost of battery-operated vehicles as well as high-performance portable consumer electronics. Nanotechnology, however, is still nascent in terms of its energy production potential.

Manufacturers have leveraged technological opportunities to produce world-changing devices but infrastructure is still catching up

The U.S. manufacturing sector is booming. The automation of production lines and the value of collocating R&D environments with production plants have underpinned a strong trend of "re-shoring" manufacturing operations back to the US. 3D manufacturing is established in industries targeting highly complex, customizable parts, while high-volume generic products are still more efficiently produced via large manufacturing facilities.

Dramatic advances in the way that machines are able to see, hear and respond to the world around them mean that electronic, autonomous vehicles (with partial self-drive functions) are commercially competitive and prominent in the automobile market. Fully driverless cars are road-ready, although infrastructure holds back their roll-out beyond small areas in cities and resorts. The legal framework for human interaction with robots and driverless cars in the U.S. is established. Public opinion over safety and the jobs impact is benign or generally supportive.

More so than driverless cars, driverless haulage vehicles have been widely taken up by the industry. Large driverless trucks transport heavy loads long distances, meeting drivers at transport nodes to "take the wheel" and complete the passage to the warehouse, before the load is broken up and driven to its final destination by smaller transit vehicles.

Drones are capable of traveling long distances as well as operating within (large) enclosed spaces. For companies in farming, extractive sectors, fishing, and in certain service sectors, such as logistics, online retail and security services, the use of drones is necessary to be able to compete in the marketplace.

The market for home services robots is also booming, thanks to low cost 3D sensors, cloud-based machine learning and advances in speech recognition. Special purpose robots clean offices, enhance security and deliver packages. In healthcare, robots interact with patients to monitor health and support care-givers.

ANNEX 2

MODELING THE LABOR MARKET IMPACT

Our modelling framework is designed to explore the implications of technological change on the shape of the U.S. labor market. It is based on a long-term assumption of equilibrium employment and therefore does not attempt to forecast fluctuations in the rate of unemployment. More importantly, we make two crucial assumptions in our modelling approach. First, we assume that households' demands are insatiable and hence consumption rises in line with incomes. Second, we assume that human workers retain comparative advantage, relative to capital, in various tasks. These two assumptions, which seem likely to hold over the timeframe of our analysis, effectively rule out the prospect of technological unemployment in our model.

Our model makes use of granular data from i) the Bureau of Labor Statistics on the structure of the U.S. labor market, distributing employment across approximately 800 occupations and 20 industries, ii) O*NET on the nature of occupations, providing a comprehensive account of the skills (35 categories) and workplace tasks[1] (41 categories) for each job, as well as other characteristics, and iii) longitudinal household survey data, revealing historical evidence of the job moves individuals tend to make in the labor market.

Our scenario projections represent a shift in employment across occupations and industries in the labor market, compared to today's equilibrium. This equilibrium is represented by headcount employment from the 2015 industry-occupation matrix of the U.S. labor market, according to the Bureau of Labor Statistics. These figures are converted into Full Time Equivalent (FTE) employment units using data from the Current Population Survey of the U.S. Census Bureau on average hours worked by each occupation and assuming a 40-hour standard working week. Our approach involves a sequence of three modelling exercises, which we set out below.

1 Referred to as "Generalised Work Activities" in O*NET

1. MODELING THE STATIC DISPLACEMENT EFFECT

The displacement effect was derived from consensus expert judgements in an interactive workshop, as described in Chapter 3. The workshop produced quantitative assumptions about the extent to which, in ten years' time, less labor will be required to generate today's level of output. In doing so, it would "displace" workers from performing specific tasks that are more amenable to automation. These "task changes" were mapped to occupations based on the task-profiles of over 800 occupations in the U.S. labor market, which were produced using O*NET data. Looking back over the past ten years we found that the historical displacement effect did not fall uniformly across the pay spectrum. Therefore, to avoid an oversimplification, the distribution of task changes was adjusted (by wage decile) to reflect historical trends.

The task profile of a given occupation[2] provides an estimate of the share of working time spent completing each workplace task (*t*). It is calculated using the relative importance (*IM*) of each workplace task, only including tasks that are deemed important for that occupation. The importance score is derived from O*NET data, which gives each task for each occupation a score from one to five. We normalize this score on a zero-to-100 scale and label all tasks with a score greater than or equal to 50 as "important" to a given occupation. By way of context, the approximately 800 occupations in the U.S. labor market involve an average of 22 "important" tasks. Food preparation workers, for example, have four important tasks to complete, whilst surveyors have 38. The estimated share of working time spent on (for example) task one for occupation (*o*) is therefore as follows:

$$(1)\ \ T_{o1} = \frac{IM_{o1}}{\sum_{t=1}^{41} IM_{ot}} \ \ where\ IM_{ot} \geq 50$$

Our expert panel produced task-specific assumptions about the change in FTE employment required to perform each task. This resulted in a new occupational task profile, where β_t is the static displacement effect[3] for task *t*.

$$(2)\ \ T_{o1}^{d} = \frac{IM_{o1}(1+\beta_1)}{\sum_{t=1}^{41} IM_{ot}(1+\beta_t)} \ \ where\ IM_{ot} \geq 50$$

The implied impact on FTE employment from the displacement effect was calculated for each occupation (ΔEmp_o^d) based on the gross reduction in FTE hours required to complete each task under the future technology scenario, compared to baseline (3). The labor market-wide impact was calculated as the sum of the occupational effects (4).

$$(3)\ \ \Delta Emp_o^d = Emp_o^d - Emp_o^{2015} \quad \text{where } Emp_o^d = \sum_{t=1}^{41} T_{ot}(1+\beta_t)\, Emp_o^{2015}$$

$$(4)\ \ \Delta Emp^D = \sum \Delta Emp_o^d$$

2 O*NET data is not industry specific, therefore the displacement effect is the same across industries for a particular occupations

3 As previously mentioned, these β_t vary by wage decile.

Whilst the expert panel dictated that most tasks would be subject to productivity gains over the next decade, i.e. would see a displacement effect, some tasks would see an increase in demand for workers as a necessary corollary of achieving those productivity gains. An example is that workers would have to 'interact more with computers' to achieve technology-based productivity gains in other tasks, such as 'inspecting equipment'. These "positive displacements" are interpreted differently to negative displacements. They are interpreted solely as a change in the task-composition of an occupation, which results in a rise in the amount of time each worker spends on that task at the expense of other tasks, such that the net FTE employment for the occupation is unchanged. Therefore, the total displacement effect for each individual occupation is always positive – in other words labor demand falls for a fixed level of output. For 'interacting with computers' specifically, an additional assumption is imposed, stating that this task becomes important for more jobs, based on an adjustment in the *importance threshold* for this task.

2. MODELING THE INCOME EFFECT

The income effect occurs as a result of increased demand for goods and services, which is caused by the higher productivity described above, and offsets the displacement effect on employment. Where that demand falls – how people spend their extra income – is independent of the sectors in which technology is generating productivity gains. To estimate this income effect, we took Gross Value Added (GVA) growth forecasts for the U.S. in 2027 from the Oxford Economics Global Industry Model and derived the implications for individual occupations using industry-occupation matrices from the U.S. Bureau of Labor Statistics.

In the real world, the displacement and income effect occur in parallel. However, technically we estimated the displacement effect of our technology scenario first. We take the post-displacement employment for occupation *o* in industry $i\ (Emp_{io}^{d})$, then apply the GVA forecast for industry (ΔGVA_i) [4] and sum across all industries to estimate the net change in employment level for occupation *o* (ΔEmp_o^{ie}).

(5) $\Delta Emp_o^{ie} = \sum_{i=1}^{19} \Delta GVA_i * Emp_{io}^{d}$

The aggregate income effect on FTE employment was calculated as the sum of all occupational impacts and, for modelling purposes, was constrained in FTE employment terms to equal the aggregate displacement effect, as expressed in (6). In fact, the income effect exceeded the displacement effect, but the residual is presumed to be driven by other, non-information technology-related productivity gains that are correlated to digitalization.

(6) $\Delta Emp^{I} = \Delta Emp^{D}$

3. MODELING THE MOVEMENT OF WORKERS

We combined the displacement and income effects to formulate a 2027 labor market forecast in which 4.3 million new job vacancies were created and 4.3 million jobs made redundant, with the resulting equilibrium having no change in the overall employment level by assumption. The

4 % growth in GVA over the next 10 years (2017-2027)

skills matching model was designed to match vacant positions in the labor market with viable candidates, and to iteratively fill vacancies until no surplus workers remained and equilibrium was restored.

3.1 PRODUCING THE PROBABILITY MATRIX

The model is designed to simulate the behavior of the labor market by tracing every movement that occurs to restore equilibrium. To do this requires estimating the probability of any given vacancy being filled by workers from every other occupation and industry. This abstracts from the normal churn that is an everyday feature of the labor market - as people move jobs and progress for reasons other than the displacement caused by technological change - by focusing only on the job moves caused by displacement owing to the technology scenario. The probabilities were calculated in two stages.

a. Broad level

At the broad level, we calculated the probability of a worker in any one occupation moving to another occupation based on historical job move data, which was taken from National Longitudinal Surveys of the Bureau of Labor Studies and the Panel Survey of Income Dynamics. Due to data constraints, it is only credible to estimate these probabilities at the two-digit industry-occupation category level, for example 'Business & Finance' occupations in the 'Mining' sector or 'Management' occupations in the 'Utilities' sector. The probability of a vacancy in the receiving industry-occupation pair (*Recipient*$_{io}$) being filled by a candidate from a sending industry-occupation pair (*Source*$_{io}$) is calculated as the incidence of that job-move as a share of all job moves into the receiving industry-occupation pair over time.

$$(7)\quad P\,(Source_{io} \rightarrow Recipient_{io}) = \frac{\sum_{Time}(Source_{io} \rightarrow Recipient_{io})}{\sum_{Ind}\sum_{Occ}\sum_{Time}(Source_{io} \rightarrow Recipient_{io})}$$

b. Granular level

In order to reach more granular breakdowns, we used occupation-specific data from O*NET to distribute the high-level moves amongst a more granular cast list. Specifically, we calculated a "distance matrix" which can be used to show the relative compatibility of any two granular occupations. The basis of our approach to calculate the "distance" scores was O*NET's career changers algorithm[5], in which the "Euclidean distance" between each pair of occupations was calculated for the following O*NET descriptors: Job Zone, Knowledge, Skills, Work Activities and Work Context. Further information about the O*NET data can be found in Annex 4. Some of the descriptors include both "importance" and "level" ratings – the latter gives each task for each occupation a score from zero to seven based on the degree to which it is required to perform the recipient occupation. For these descriptors, the average of the two was taken. The Euclidean distance between occupation x and y for the descriptor Skills is calculated as follows:

$$(8)\quad d(x,y)_{Skills} = \frac{\sqrt{\sum_{k=1}^{K}(x_k - y_k)^2}}{K} \quad where\ K = the\ number\ of\ characteristics$$

5 "Development and evaluation of a new O*NET related occupations matrix" (2012)

The "distance" score between two occupations (x and y) is calculated as the average distance across the five O*NET descriptors mentioned above. If the overall distance between two occupations, or the distance on an important characteristic, is too large, that move is deemed infeasible and therefore the probability of that move occurring is assumed to be zero. For example, the direct path between a Cabinet Maker and a Physicist would be deemed infeasible, no matter how many vacant Physics positions there were, because the distance the Cabinet Maker would have to make up in Science and Mathematics skills would be too great. The "distance" scores are then inverted to show the "compatibility" between two occupations rather than the "distance", such that a higher score indicates the occupations are more similar, and hence moves between them more likely.

This enabled us to derive the likelihood of moves between any two granular SIC-SOC[6] cells. This level of detail takes us beyond the compatibility of jobs at the two-digit SOC code level, to the compatibility of six-digit SOC code occupations below it, for example 'Accountants' in the 'Mining' sector or 'Marketing Managers' in the 'Utilities' sector. It is this granular probability matrix that is used within the Skills Matching Model.

3.2 SKILLS MATCHING MODEL

The Skills Matching Model was designed to match vacant positions in the labor market with viable candidates, iteratively filling the vacancies until no surplus workers remain and equilibrium is restored. The matching algorithm considers both the viability of a move from one occupation to another in terms of job compatibility, as well as the wage dynamics that would play out in practice, to incentivize the movement of labor in the evolving economy.

Changes in the demand and supply of labor brought about by the displacement and income effects will affect wages in each occupation. For occupations that experience high growth in labor demand, wages will be expected to rise and the probability of workers in those occupations wanting to move will fall. For occupations that experience a large reduction in labor demand, the opposite will happen: workers in these occupations will be willing to accept lower wages and they will be more likely to move jobs.

These dynamics are embedded in the historical job moves data to an extent, but given the uniqueness of the labor market "shock" we are modelling (in which we process ten years' worth of technological change concurrently), the wage dynamics surpass those experienced in the past. For that reason, we incorporate a Wage Adjustment Factor (WAF_i^j) into the model equation. The WAF for a sending occupation (i), in the context of a move to a receiving occupation (j), reflects the difference in wage pressures between the two, relative to the wage pressure being felt in other, competing, sending occupations[7]. When the difference in wage pressure between a receiving and sending occupation is greater than the average wage pressure differential related to that receiving occupation, the WAF will be greater than one,

6 Two digit SIC and six digit SOC
7 Relative wage-adjustment factors are constrained so the probabilities sum to 100%

and the likelihood of that move taking place will therefore be greater than the historical data suggests. When the relative wage pressure is smaller than average for a move to the receiving occupation, the WAF will be less than one and the likelihood of the move taking place will therefore be lower than historical data suggests.

(9) $$WAF_i^j = \frac{\%\Delta Emp_j - \%\Delta Emp_i}{\frac{1}{M}\sum_{i=1}^{M}(\%\Delta Emp_j - \%\Delta Emp_i)} \quad \text{where M} = \text{number of potential sending occupations}$$

The model solves iteratively by filling one vacancy[8] at a time and recalculating the relative wage-adjustment factors after each iteration. Each iteration starts by taking the occupation with the greatest upward wage pressure (i.e. the greatest proportion of vacancies), calculating the relative wage-adjustment factors for all potential sending occupations and therefore deriving the probability that the vacancy is filled by those occupations. Once that vacancy is filled, the wage pressure experienced by that occupation will fall. Therefore, the wage pressure is recalculated and the next iteration begins. The model will step through each iteration until all vacancies have been filled and the labor market has returned to equilibrium.[9] As wage pressures dissipate, the WAF tends to one, meaning the probability matrix tends back to historical probabilities.

8 Due to computational constraints 10% of the initial required vacancies for a given occupation are filled in each iteration rather than one single vacancy.

9 In order to prevent workers moving back and forth between occupations, a rule was set up that prevents a vacancy being filled by an occupation with a similar wage pressure.

ANNEX 3

MODELING THE "HOLLOWING OUT" EFFECT

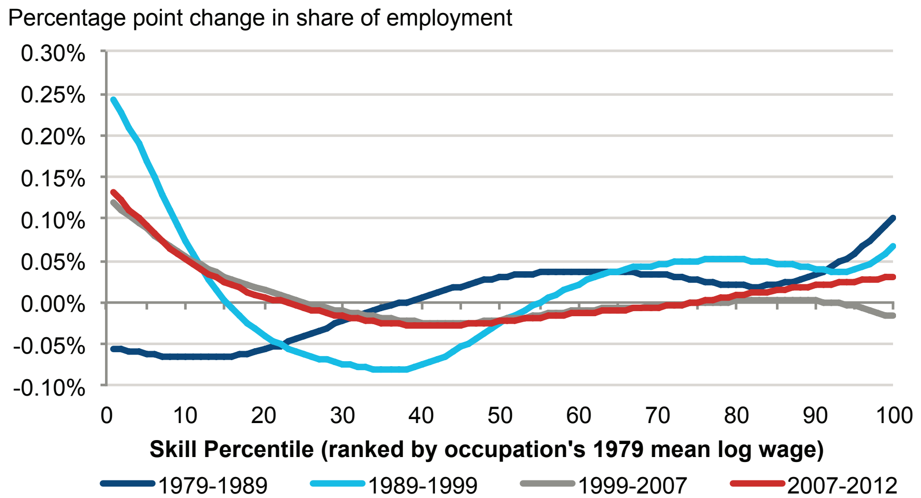
In this research project, we set out to forecast how the shape of the labor market will change over the next ten years in response to a changing technological landscape. To ensure the credibility of our results we grounded our analysis in the existing literature by comparing our forecast with historically observed trends. One of the most prominent studies of the impact of technological change on the labor market was produced by David Autor, Frank Levy and Richard Murnane in 2003[1], and later followed up by Autor in 2015.[2] These studies identified a trend in which technological innovations were "hollowing out" the labor market over time, captured by the rising share of employment in low- and high-skilled occupations at the expense of mid-skilled occupations. This trend was observed across consecutive time periods. Just as noteworthy was the observation that this U-shaped pattern has been shifting further up the skills-spectrum over time, perhaps explained by increasingly powerful technology competing with workers in increasingly skilled occupations.

To provide a basis for our own analysis, we set out to recreate the historical "Autor curves" and to contrast our labor market projections for the next ten years with the trends observed in the past. We present our replication of these curves in Fig. 25, plotting the smoothed change in employment shares by occupational skill percentiles, ranked by occupation's mean log wage in the *Census IPUMS 1980 five percent extract.*

1 Autor, D. H., Levy, F. & Murnane, R. J. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics,* 118(4): 1279–1333.

2 Autor, D. (2015) "Why Are There Still So Many jobs? The History and Future of Workplace Automation" Journal of Economic Perspectives, Vol. 29, no. 3, Summer, pp. 3–30

Fig. 25 Historical shifts in employment across the skills spectrum, 1979-2012



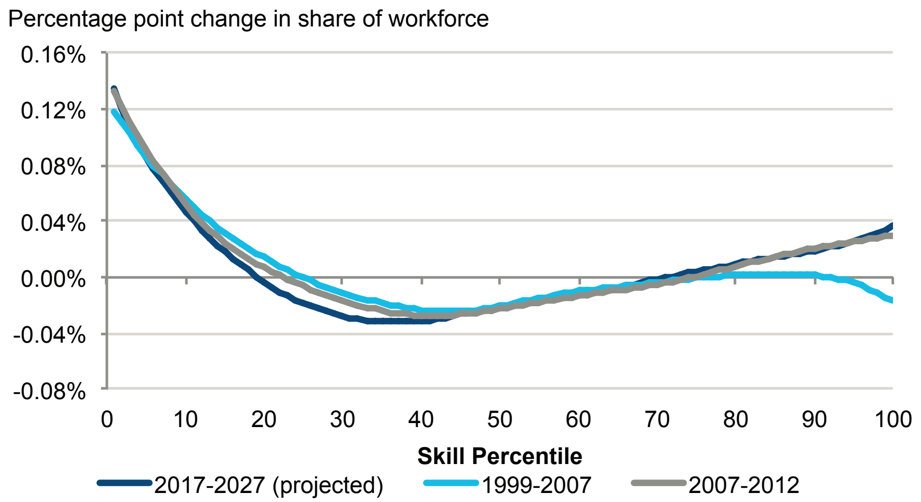
Source: Oxford Economics, American Community Survey, IPUMS

To place our ten-year future projection into the context of Autor's work, we followed a similar approach. Occupations were first ranked into skill percentiles according to their mean 2015 wage, which was taken from the Occupational Employment Statistics (OES) database of the Bureau of Labor Statistics (BLS). For 6-digit occupations without wage data, we progressively moved up to higher levels of aggregation until we could impute the data gaps.*

Employment shares by skill percentile were calculated using full time equivalent (FTE) employment. Headcount employment by occupation for 2015 was obtained from the OES and converted into FTE employment using data from the Current Population Survey of the U.S. Census Bureau on average hours worked by each occupation and assuming a 40-hour standard working week. In line with Autor, the change in employment share by skill percentile over our forecast period is smoothed using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations).

* We started with 5-digit SOC codes and aggregated up further if required. The highest level of aggregation used was 3-digit SOC codes.

Fig. 26 Projected vs historical shifts in employment across the skills spectrum, 1999-2027

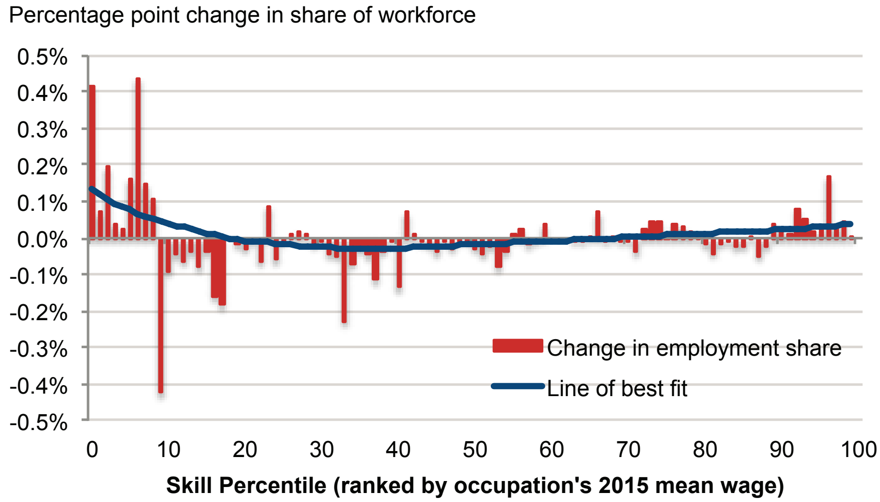


Source: Oxford Economics, American Community Survey, IPUMS, BLS, Current Population Survey

Our projected “hollowing out” curve is presented in Fig. 26 alongside our historic “hollowing out” curves for the two latest periods (1999 to 2007 and 2007 to 2012). Note that the skill percentiles are different between our projected curve and the historical curves. The projected curve uses skill percentiles ranked by the occupation’s 2015 mean wage, whereas the historical curves use skill percentiles ranked by the occupation’s 1979 mean log wage.

Our analysis implies that there will be a continuation of the hollowing out effect over the next ten years. But the severity of the effect will not materially worsen compared to the recent time periods studied and we do not observe a significant shift rightward, up the skill-spectrum, to higher skilled jobs. The impact is more nuanced than this smoothed line of best fit depicts – there are positive and negative implications for occupations along the length of the entire skills spectrum. This more nuanced picture is illustrated in Fig. 27 below. Each bar represents the (non-smoothed) projected change in employment share by skill percentile. This demonstrates how some occupations at the higher and lower ends of the spectrum are projected to experience a decline in employment share and some occupations in the middle are projected to grow their share of employment.

Fig. 27 Projected shift in employment across skills spectrum, by percentile of workforce, 2017-2027



Source: Oxford Economics, BLS, Current Population Survey

The charts that we present in the main report, in Fig. 1 and Fig. 19, are adapted from the charts above to present a more intuitive result. When recreating Autor's curves, we sought to analyze the shift in employment by percentile of the workforce, determined by ranking occupations according to their wage levels and dividing them into 100 cohorts. This was useful for consistent comparison with the past but presented some problems in interpretation. The ranked occupations obscure the varying levels of employment in each occupation – an occupation at one percentile could be a huge employer while the next percentile's occupation could cover only a tiny portion of the workforce. Secondly, the smoothed curve obscures the more nuanced implications for employment change across the labor market, implied by Fig. 27.

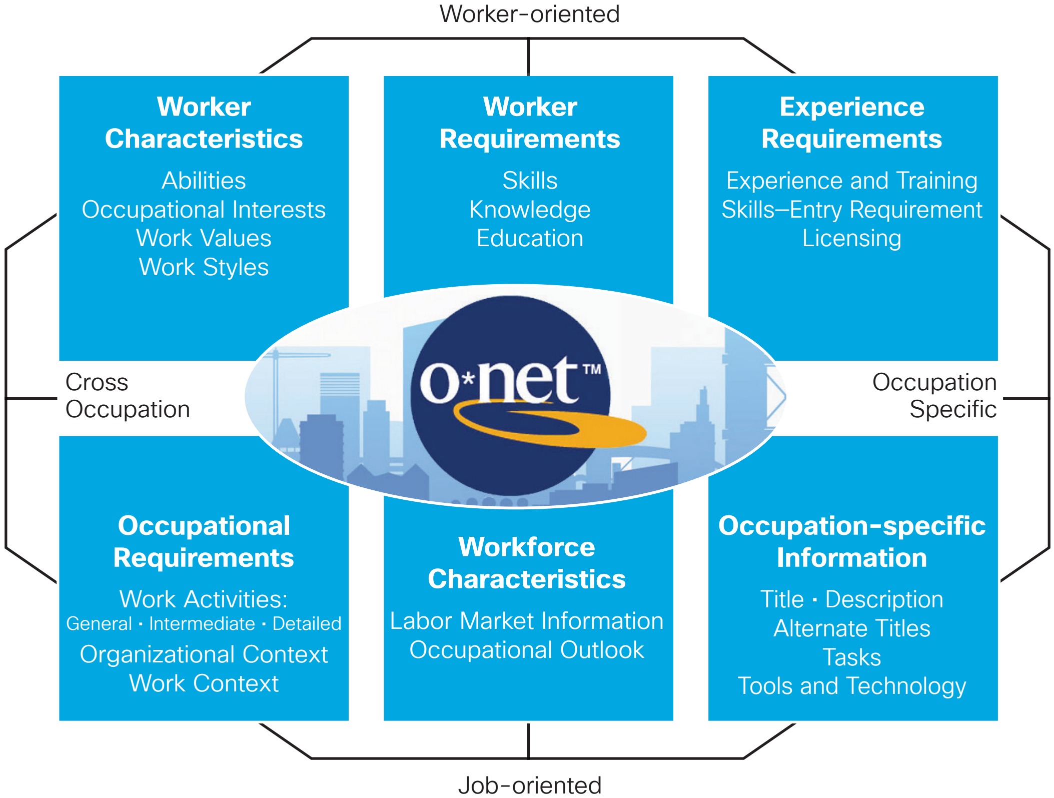
We therefore weighted the ranked occupation by employment share instead, making it more intuitively representative of the labor force, and reformulated the curve by aggregating employment shares into ventiles (five percentile aggregates) as well as smoothing the curvature over a shorter bandwidth (i.e. using a locally weighted smoothing regression with bandwidth 0.4 for 20 observations), to better represent the variation in employment effects across the skills spectrum.

ANNEX 4

WHAT IS O*NET AND HOW DID WE USE IT?

The U.S. O*NET program is a comprehensive system for collecting and disseminating information on occupational and worker characteristics, sponsored by the U.S. Department of Labor and Employment and Training Administration. At the center of the program is the O*NET database, which contains information on hundreds of standardized and occupation-specific descriptors for over 1000 different occupations. All of these data are structured according to the O*NET "content model", which defines the key features of an occupation as a standardized set of variables called "descriptors". The descriptors are meant to provide an exhaustive list of all the worker characteristics, worker requirements and occupation requirements for any given occupation. Information is organized across six "domains" which comprise both worker-oriented characteristics and job-oriented characteristics. Please see table below for illustration of the "content model".

Much of the information is collected via self-reported assessments by existing employees using standardized questionnaire surveys, and is supplemented by professional assessments by job evaluation analysts. These data collection methods are undertaken on an ongoing basis, enabling information to be updated regularly, and has created a rich time-series database of occupation-specific descriptors spanning almost 20 years.



For this paper, the core data used from the O*NET database were the "Skills" and "Generalized Work Activities" sections. For both of these elements of the database, the "Importance" and "Level" of each skill or characteristic is recorded. The former reflects the degree of importance a particular descriptor has to the occupation and is scored from one ("not important") to 5 ("extremely important"). The latter reflects the degree to which a particular descriptor is required to perform the occupation. It is scored according to a 0-7 scale with reference points (or "level anchors") to help respondents place a value on that range.

The descriptors included in both of these sections are meant to be exhaustive and mutually exclusive. For example, the 35 skill descriptors should provide a comprehensive list of all the skills that might be required by a worker in any given occupation in the US. The table below presents the typology used for the "Skills" and "Generalized Work Activities" sections of the O*NET database.

O*NET Skills typology

Category	Descriptor
Basic Skills	Active Learning
	Active Listening
	Critical Thinking
	Learning Strategies
	Mathematics
	Monitoring
	Reading Comprehension
	Science
	Speaking
	Writing
Social Skills	Social Perceptiveness
	Coordination
	Persuasion
	Negotiation
	Instructing
	Service Orientation
Complex Problem Solving	Complex Problem Solving
Technical Skills	Operations Analysis
	Technology Design
	Equipment Selection
	Installation
	Programming
	Operation Monitoring
	Operation and Control
	Equipment Maintenance
	Troubleshooting
	Repairing
	Quality Control Analysis
Systems Skills	Judgement and Decision Making
	Systems Analysis
	Systems Evaluation
Resource Management Skills	Time Management
	Management of Financial Resources
	Management of Material Resources
	Management of Personnel Resources

O*NET Work Activities (tasks) typology

Category	Descriptor
Information Input	Getting Information
	Monitoring Processes, Materials, or Surroundings
	Identifying Objects, Actions, and Events
	Inspecting Equipment, Structures, or Material
	Estimating the Quantifiable Characteristics of Products, Events, or Information
Mental Processes	Judging the Quality of Things, Services, or People
	Processing Information
	Evaluating Information to Determine Compliance with Standards
	Analyzing Data or Information
	Making Decisions and Solving Problems
	Thinking Creatively
	Updating and Using Relevant Knowledge
	Developing Objective and Strategies
	Scheduling Work and Activities
	Organizing, Planning, and Prioritizing Work
Work Output	Performing General Physical Activities
	Handling and Moving Objects
	Controlling Machines and Processes
	Operating Vehicles, Mechanized Devices, or Equipment
	Interacting with Computers
	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
	Repairing and Maintaining Mechanical Equipment
	Repairing and Maintaining Electronic Equipment
	Documenting/Recording Information
Interacting with Others	Interpreting the Meaning of Information for Others
	Communicating with Supervisors, Peers, or Subordinates
	Communicating with Persons Outside Organization
	Establishing and Maintaining Interpersonal Relationships
	Assisting and Caring for Others
	Selling or Influencing Others
	Resolving Conflicts and Negotiating with Others
	Performing for or Working Directly with the Public
	Coordinating the Work and Activities of Others
	Developing and Building Teams
	Training and Teaching Others
	Guiding, Directing, and Motivating Subordinates
	Coaching and Developing Others
	Provide Consultation and Advice to Others
	Performing Administrative Activities
	Staffing Organizational Units
	Monitoring and Controlling Resources

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