FEDERAL RESERVE BANK OF PHILADELPHIA

AUTOMATION AND REGIONAL EMPLOYMENT IN THE THIRD FEDERAL RESERVE DISTRICT

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INTRODUCTION

Automation, enabled by artificial intelligence, robotics, and other technological advancements, is rapidly changing people's jobs and lives. Automation has the potential to improve productivity and allow workers to focus on safer, more productive, and more creative tasks. However, people are concerned about the risk of job losses and increased income inequality due to the wide adoption of automation technologies.

Automation is capable of replacing many tasks that follow well-defined procedures and even certain complicated tasks where learning and judgement are required. Certain jobs thus could become entirely redundant as more work is done by computers or robots. In addition to job replacement concerns, automation could lead to increased inequality if it reduces demand and wages for low-skill jobs while the displaced workers from these occupations have greater difficulty in adapting to a job market undergoing rapid technological progress.

However, less attention is paid to the job opportunities for workers whose jobs are at risk of automation. Automation could lead to significant job losses, but new jobs will be created, and workers thus will have the opportunity to switch occupations. It is important to understand where job growth will occur and under what conditions there could be enough new jobs for displaced workers. In addition, most studies provide a global or national perspective on the impact of automation — fitting, since the global economy has become more interdependent. However, there is little guidance on the implications of these national findings for practitioners and policymakers at the local level, as automation's effects on work will likely differ across regions. This study intends to shed light on these issues using existing data and evidence.

Focusing on 11 metropolitan statistical areas (MSAs) within the Third Federal Reserve District (Third District), which covers eastern Pennsylvania, southern New Jersey, and Delaware (Figure 1), this report analyzes the risk of automation for various occupations in the workforce and the potential need to make workforce transitions to inform current debates on how to improve and strengthen our regional economy.

Numerous scholars, thought leaders, and popular writers have attempted to identify the occupations that will be most affected by automation, as well as the magnitude of that impact.

Our inquiry seeks to answer:

- Who will be most impacted by automation? How will the effects of automation vary by different demographic groups based on gender, race/ethnicity, educational attainment levels, income, age, and across different geographic areas in the Third District?
- Are there going to be enough new jobs for displaced workers? To what extent and under what conditions will the negative employment impact of automation be mitigated by employment growth?
- What will be the new jobs? How can we connect at-risk workers with new job opportunities?

Predicting the impact of technologies on job losses, however, is an impossible task, since it is always difficult to forecast where technological innovations will be and whether and how fast those innovations will be widely adopted. Instead of focusing on the levels of the automation impact alone, we use data provided by Frey and Osborne (2017) to illustrate the potentially heterogeneous effects of automation on regional employment. The Frey and Osborne data, although not perfect, provide detailed information of automation probability at the occupation level. Taking a relatively conservative approach, we assume that only the jobs with the highest risk rating (95 percent or higher) have a risk of being replaced in the next decade by currently demonstrated technologies. Some examples of high-risk jobs include cashiers, bookkeepers, receptionists, landscapers, office clerks, loan officers, and bank tellers (see the top high-risk occupations in Table 1 and Table A1 in the Appendix).

Based on our definition, we estimate that 18.2 percent — or about 25 million jobs in the United States — are at a high risk of being replaced by automation; another 30.4 percent are at some risk of automation (70–94 percent), potentially experiencing significant changes in the tasks and skills required for the job.

The numbers are 18.3 percent, or over 800,000 jobs, at a high risk of automation for MSAs in the Third District and 17.9 percent, or almost half a million jobs, in the Philadelphia-Camden-Wilmington (Philadelphia hereafter) MSA alone. Automation's effects on jobs differ across metropolitan areas. Relatively wealthier areas, such as the Philadelphia and Trenton MSAs, have the lowest share of jobs at a high risk of automation, whereas areas with lower wages are more likely to be hit harder by the coming changes, with the Altoona MSA having the highest share (21.6 percent) of jobs at a high risk of automation.

Despite these real risks to workers, adopting automation technologies takes time; more realistically, only a fraction of the workers in high-risk occupations will lose their jobs in the near future. Some high-risk jobs will never be automated because of the lack of economic feasibility, as well as legal, technological, and social obstacles. More important, new jobs will be created via economic growth, innovation, and investment to accommodate workers displaced by automation. We use state-level Bureau of Labor Statistics (BLS) data and a very simplified method to evaluate the future job opportunities for workers at risk of job automation. Specifically, we calculate a *breakeven adoption ratio* to roughly measure an area's susceptibility to automation, by dividing the net job growth rate projected by BLS by the high-risk job share. For example, in the Philadelphia MSA we divide the net job growth rate of 6.2 percent by the high-risk job share of 17.9 percent to yield a breakeven adoption ratio of about one-third (34.7 percent). This means that in the Philadelphia MSA, as long as fewer than approximately one out of three workers holding high-risk jobs lose their jobs in the next decade or so, there could be enough new jobs available to workers displaced by automation.[1] This breakeven adoption ratio varies from 25 percent to 44 percent in different MSAs. Areas with higher wages, such as the Philadelphia and Trenton MSAs, have relatively higher values because they have more new job opportunities and fewer jobs at risk of automation, whereas lower-wage MSAs are likely to have greater difficulty generating enough new jobs for displaced workers. Of course, high-risk occupations in relatively wealthier areas may be hit harder by the coming technological changes as well, as higher average wages incentivize automation in order to reduce costs.

Just as we see regional variations, automation will not impact every worker equally, which raises equity concerns. On average, lower-paid occupations, as well as occupations requiring less education, have much higher risks of automation.

In the Philadelphia MSA, over one-quarter (26.2 percent) of workers in occupations requiring a high school diploma or less are at a high risk of automation, while very few (1.4 percent) high-skill occupations (requiring a bachelor's degree or higher) are at a high risk. Similarly, female, minority, and younger and older workers are more susceptible to automation than others. This highlights the risk that going forward, less advantaged populations may suffer more in the labor market as automation progresses — in other words, inequality may rise. Of course, the risk of job losses may not become manifest for many less advantaged workers in low-skill, high-risk occupations in the near future. The adoption of automation will be a long-term and gradual process, and the relatively lower wages of many low-skill jobs provides less economic incentive for firms to adopt labor-replacing technologies, likely providing sufficient time for vulnerable workers to adjust. The demand for low-skill occupations may even increase in the short term because of the economic recovery, and technological progress could generate new labor-demanding tasks as well (Autor and Salomons, 2018).

In the long run, however, less advantaged populations who are already in a vulnerable position in the labor market could be hit harder by automation without assistance to develop new skills or obtain a higher education credential to transition to new jobs. We highlight potential jobs available for displaced workers; both new and existing jobs with lower risks of automation require much higher levels of educational attainment and skills. While high-income, high-skill workers are more able to adapt to a rapidly changing job market, low-skill workers are more likely to find themselves either facing an increasing risk of their jobs being replaced by automation or being ill-prepared for new job opportunities. Policymakers, institutions, and individuals need to be better prepared to deal with future large-scale workforce transitions for both those who are at risk of being displaced and those who manage to keep their jobs but need to adapt to the new tasks. Individuals and areas that fail to manage this transition could see rising unemployment and increased inequality.

In the following report, we first examine who will be most impacted by a high risk of automation. We then discuss potential areas for employment growth and opportunities associated with automation. We conclude with a discussion on the implications that impending automation has for both policymakers and practitioners. Detailed data for individual MSAs can be found in Appendix A, while a discussion of data and methods used throughout the report are compiled in Appendix B.

AUTOMATION AND JOBS

What Do We Know?

Globally, technological advancement is gradually restructuring labor markets (World Bank, 2016) and contributing to rising income inequality (Autor, Katz, and Kearney, 2006). Labor markets are also becoming increasingly polarized, with higher shares of employment occurring in high-skill or low-skill jobs, but with decreasing shares in middle-skill employment (Acemoglu and Autor, 2010; Autor et al., 2006).

Researchers are particularly interested in whether automation will be labor-displacing or labor-augmenting (Autor, 2015; Autor and Salomons, 2018). As summarized by Furman and Seamans (2018), automation could have several effects on labor markets. First, automation can displace a job entirely in an affected sector. Second, automation can create new jobs in existing occupations or unknown new jobs. Third, higher incomes from improved productivity can increase demand for jobs throughout the economy, such as in leisure and hospitality industries, as people may have resources to spend on such activities. Finally, technology may replace the specific tasks of a job rather than the entire job itself and fundamentally shift the way the job is conducted as people interact with the new technology.

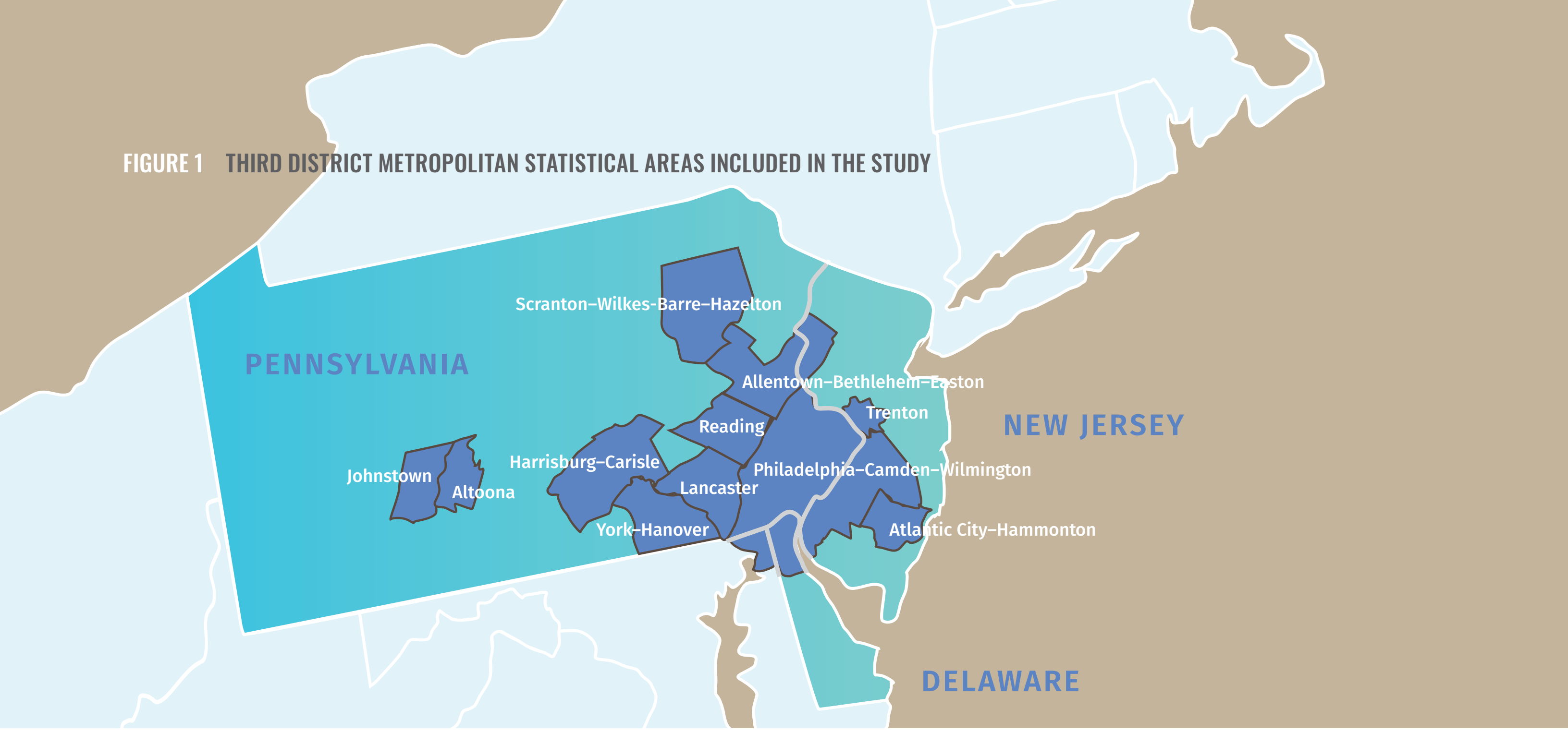
Predictions about the scope of job replacement vary widely. Frey and Osborne (2017) produced a foundational study classifying 702 occupations in the U.S. based on their susceptibility to automation. The authors, along with a team of machine learning researchers, both hand-labeled a subset of 70 occupations as either automatable or not while also comparing these subjective comparisons with task-level complexity measures. Employing machine learning techniques, probabilities of automation for all occupations were calculated from the subset of coded data. They estimated that about 47 percent of the 2010 jobs in the U.S. are at risk of automation because they involve work that can be easily automated. In contrast, a study by the Organisation for Economic Co-operation and Development (OECD) argues that only 9 percent of jobs in the U.S. are at risk of being fully automated (Arntz, Gregory, and Zierahn, 2016). It argues that automation targets tasks rather than occupations, which are themselves particular combinations of tasks. Many occupations are likely to change as some of their associated tasks become automatable, so it concludes that relatively few occupations will be entirely automated. The McKinsey Global Institute also conducted a similar study, estimating that for about 60 percent of occupations in the U.S., 30 percent of tasks are potentially automatable (Manyika et al., 2017a). It assumes that single-job tasks, rather than whole occupations, are automated by technology. And in a companion study, Manyika et al. (2017b) estimate that 23 percent of the work hours in the U.S. could be replaced by automation by 2030.

Robots welding in a car factory. Photographer: WangAnQi for Getty Images

Despite the known risks associated with job automation on employment, automation could also lead to potential economic benefits and job growth (Autor, 2015; Furman and Seamans, 2018; Manyika et al., 2017b). For instance, technological advancement measured by the adoption of robotics for certain functions is often linked to increases in economic productivity (Furman and Seamans, 2018), especially in sectors that have unmet demand in the labor market (Bessen, 2018). For regions more amenable to adopting these technologies, increased economic growth, when equally distributed, could counteract potential job losses. Bessen (2018) argues that labor demand will determine where automation will impact job losses. If automation is targeted at industries that have already automated previously in some way through other computing technologies, demand for those jobs will be relatively the same or decline. But, if new technologies create entirely new services, demand for those services may increase and therefore provide more employment opportunities. Instead of generating estimates of job growth, Autor and Salomons (2018) show all the paths through which technology can affect labor demand are in general equilibrium. They find evidence that automation has not been job-displacing but has reduced labor's share of value added. They suggest that automation can result in net job growth, mostly in industries supplying automation technologies that counterbalance employment decline in other industries.

Korinek and Stiglitz (2017) suggest the primary economic challenge posed by the adoption of artificial intelligence will be inequality, which could rise because innovators earn a surplus from technological innovations and because innovations change the demand for labor (and capital), which affects both employment and workers' wages. Even if automation does not lead to technological unemployment, new technologies may also result in wage declines for lower-skill workers rather than complete job loss. While more jobs may be created, some workers may be compensated less for their work, thus contributing to increasing inequality (Autor and Salomons, 2018; Manyika et al., 2017b; Violante, 2008). Most recent studies have documented a strong negative relationship between jobs of high risk of automation and income and education (Furman and Seamans, 2018), raising concerns about automation-induced inequality.

FIGURE 1 THIRD DISTRICT METROPOLITAN STATISTICAL AREAS INCLUDED IN THE STUDY



Source: U.S. Census Bureau Cartographic Boundary Shapefiles, 2017

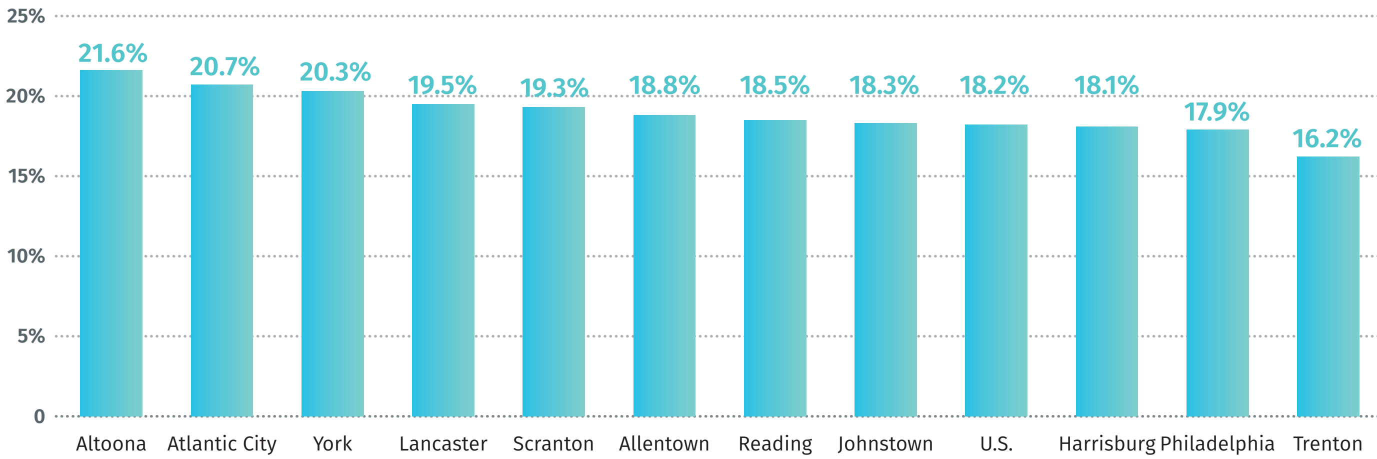
1 WHO WILL BE MOST IMPACTED BY AUTOMATION?

In general, the types of tasks involved in particular occupations make some occupations more susceptible to automation than others. Building on Frey and Osborne's (2017) work estimating the probability of job automation for different occupations, job automation is defined on a spectrum of more or less risk for automation. We define jobs with a 95 percent or greater likelihood of being automated as *high-risk* jobs for automation. A relatively higher cutoff point of 95 percent is used to reduce the risk of misclassifying occupations in which only certain job tasks are automatable by existing technology.[2] While the cutoff point is somewhat arbitrary, the focus of this exercise is on the variation of automation's effects across geography and subpopulations, instead of the absolute levels (see the top high-risk occupations in Table 1 and Table A1 in the Appendix).[3]

Jobs *at risk* for automation are defined as those that have a 70–94 percent chance of automation. Although these jobs are still threatened by automation, we argue it is very likely that only certain tasks of these jobs are at risk of automation and there is potential that people who hold these jobs can learn the new skills required to adjust to changes in job content and still maintain employment. Examples of such jobs include automotive repair workers, retail salespersons, truck drivers, construction laborers, or carpenters. *Low-risk* jobs refer to occupations with less than 70 percent likelihood of automation. These occupations, such as nurses, teachers, arts and design workers, scientists, and managers, are the least likely to be threatened by automation over the next 10–20 years and are relatively likely to continue seeing sector growth. Accordingly, we assume only some jobs at a high risk of automation will be fully replaced by automation, while there will be no net losses and possibly job growth in at-risk or low-risk occupations.

Across all MSAs in the Third District, approximately 18.3 percent of jobs have at least a 95 percent risk or greater of being automated, slightly higher than the U.S. average of 18.2 percent. The risk of job automation is not equally distributed among different groups of people within and across each MSA. Geographic differences in job availability, access to training, economic productivity, and other historical barriers to opportunity suggest that inequities may be built into who holds more automatable jobs or who can gain the skills needed to hold more secure jobs. We describe these differences across geography and by gender, race/ethnicity, education level, wage levels, and age, focusing most on trends for those groups with disproportionate shares of workers in high-risk jobs.

FIGURE 2 SHARE OF JOBS WITH A HIGH RISK OF AUTOMATION, THIRD DISTRICT MSAs AND U.S.



Sources: Authors' calculation based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

TABLE 1 TOP 20 OCCUPATIONS WITH A HIGH RISK (≥95%) OF AUTOMATION IN THE UNITED STATES

SOC CODE	OCCUPATION TITLE	TOTAL EMPLOYMENT 2016	MEDIAN ANNUAL INCOME ($)	ENTRY-LEVEL EDUCATIONAL REQUIREMENT	PROBABLITY OF AUTOMATION
41-2011	Cashiers	3,541,010	20,108	No formal educational credential	97%
43-9061	Office Clerks, General	2,955,550	30,508	High school/GED	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Exec	2,295,510	34,820	High school/GED	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1,566,960	38,390	Some college/no degree	98%
35-2014	Cooks, Restaurant	1,217,370	24,140	No formal educational credential	96%
51-2092	Team Assemblers	1,112,780	30,060	High school/GED	97%
43-4171	Receptionists and Information Clerks	997,770	27,920	High school/GED	96%
37-3011	Landscaping and Groundskeeping Workers	906,570	26,320	No formal educational credential	95%
43-5071	Shipping, Receiving, and Traffic Clerks	676,990	31,180	High school/GED	98%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	518,950	36,780	High school/GED	98%
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	499,550	19,970	No formal educational credential	96%
43-3071	Tellers	496,760	27,260	High school/GED	98%
43-3021	Billing and Posting Clerks	485,220	36,150	High school/GED	96%
41-2021	Counter and Rental Clerks	450,330	25,550	No formal educational credential	97%
53-3031	Driver/Sales Workers	426,310	22,830	High school/GED	98%
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	404,360	19,980	No formal educational credential	97%
51-9111	Packaging and Filling Machine Operators and Tenders	386,520	28,290	High school/GED	98%
47-2073	Operating Engineers and Other Construction Equipment Operators	356,750	45,890	High school/GED	95%
13-2072	Loan Officers	305,700	63,650	Bachelor's degree	98%
43-3011	Bill and Account Collectors	298,960	35,3500	High school/GED	95%

Note: See Frey and Osborne (2017) for the probability of automation for all detailed occupations

Sources: Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

Lower-Wage MSAs Have More High-Risk Jobs for Automation Than Wealthier MSAs

The results suggest that certain places are likely to be hit harder than others by job automation in the coming decades (see Figure 2 and detailed data in Table A2). This analysis focuses on 11 major MSAs in the Third District, with the Philadelphia and Trenton MSAs being the larger and relatively wealthier ones. Lower-wage MSAs in the Third District, such as Altoona and York–Hanover, as well as places like Atlantic City–Hammonton that have slightly higher incomes but larger shares of low-skill routine jobs, all have larger shares of jobs at high risk for automation (21.6 percent, 20.3 percent, and 20.7 percent, respectively). In contrast, larger and relatively wealthier MSAs with more skilled workers, such as the Philadelphia and Trenton MSAs, are more resilient to job automation, with the lowest portion of jobs at a high risk for automation (17.9 percent and 16.2 percent respectively).[4]

These estimated shares of high-risk jobs, however, must not be equated with actual or net employment losses from automation for three reasons. First, the adoption of automation technologies will be a long-term process with lots of uncertainty, owing to various technical, economic, legal, and societal hurdles. Second, even when automation makes business sense and there are no regulatory or other barriers, adoption can take time. Finally, even if new technologies are introduced, new and additional jobs will be generated, and displaced workers may find new jobs by switching their occupations, instead of ending up in technological unemployment. So, it is reasonable to expect that only a fraction of the workers in high-risk occupations will lose their jobs in the near future, and many of them could be able to find new jobs.

FACTORS AFFECTING ADOPTION OF AUTOMATION

Here are a few important factors identified in the literature (Furman and Seamans, 2018; Manyika et al., 2017a, 2017b) that likely influence the extent and pace of adoption of automation across countries or regions:

Economic structure and mix of occupation:
The mix of economic sectors and the mix of jobs within each sector determine automation's potential and the pace of adoption. Regions with a high concentration of sectors that are highly automatable, such as manufacturing, will face a higher risk of automation. In contrast, areas with more high-skill jobs (e.g., IT professionals, scientists, teachers, managers) are less susceptible to automation.

Technological feasibility:
Technologies should be mature enough for large-scale adoption. The cost of both hardware and software should also be low enough. Technology that is capable of automating certain tasks also needs to be adapted for specific use cases. At the local level, a region's innovation capacity and IT infrastructure will likely influence the pace of deployment for various automation technologies.

Economic feasibility:
Companies adopt automation technologies to replace humans because it makes business sense: The economic benefits of reduced labor costs and improved productivity from adopting automation should outweigh the deployment costs. Wage rates of workers in at-risk occupations will be an important determinant of automation across sectors and regions. Higher labor costs in an area thus make automation more economically attractive and provide companies stronger incentive to adopt automation to reduce labor costs.

Regulatory and social hurdles:
Even without any technical and economic hurdles, legal and ethical obstacles may prevent the implementation of a particular automation technology or substantially slow the pace of adoption. Government policy can slow adoption, and social preferences could play a role in deciding whether certain tasks can be automated. For example, society may feel uncomfortable letting machines, instead of humans, make life-and-death decisions, such as when a pilotless plane needs to make an emergency landing or when robots perform critical surgeries in a hospital.

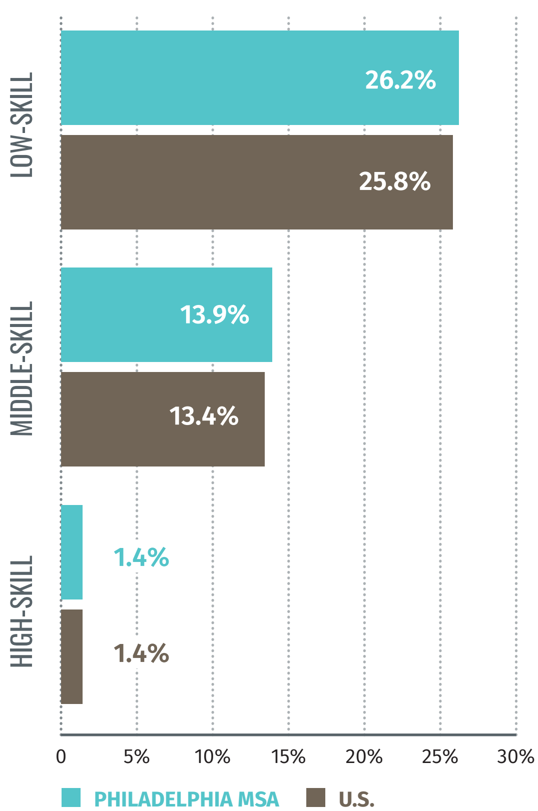
Low-Skill Workers Generally Hold Higher Shares of High-Risk Jobs, But Some Middle-Skill Jobs Are Threatened, Too

We estimate shares of jobs in three categories of educational attainment based on entry-level occupation requirements provided by the BLS: low-skill, middle-skill, and high-skill. Low-skill jobs require a high school diploma or less, while middle-skill jobs include those requiring a certificate or other nondegree credential, some college, or an associate's degree. High-skill jobs are those that require at least a bachelor's degree. By and large, low-skill jobs are most likely to have a high risk of automation (Figure 3). For instance, in the Philadelphia MSA, about 26.2 percent of low-skill jobs are at a high risk of job automation, compared with about 13.9 percent of middle-skill jobs and just 1.4 percent of high-skill jobs. Similar patterns hold for other MSAs in the Third District and the nation. In the U.S., 25.8 percent of low-skill jobs, 13.4 percent of middle-skill jobs, and 1.4 percent of high-skill jobs are at a high risk of automation.

Low-Paid Workers Are at Much Higher Risk of Having Their Jobs Automated

Based on annual median wage levels broken into income quintiles, occupations that pay roughly $36,000 a year or less are most at risk for automation across all MSAs in the Third District and the nation (Figure 4). In the Philadelphia MSA, occupations making between $27,001 and $36,000 a year have the highest risk of automation (about 35.1 percent), while the highest-wage jobs (making more than $62,000) have the lowest risk (just 0.7 percent). Low-wage workers likely have the most to lose as automation continues to change the content and focus of different occupations. These patterns are even starker for the nation — about 37.2 percent of workers making between $27,001 and $36,000 are at a high risk of automation, compared with just 0.5 percent of those making above $62,000. Of course, compared with that of high-wage occupations at similar risk, the automation of low-wage jobs may be slower because they provide less economic benefits from the reduced labor costs.

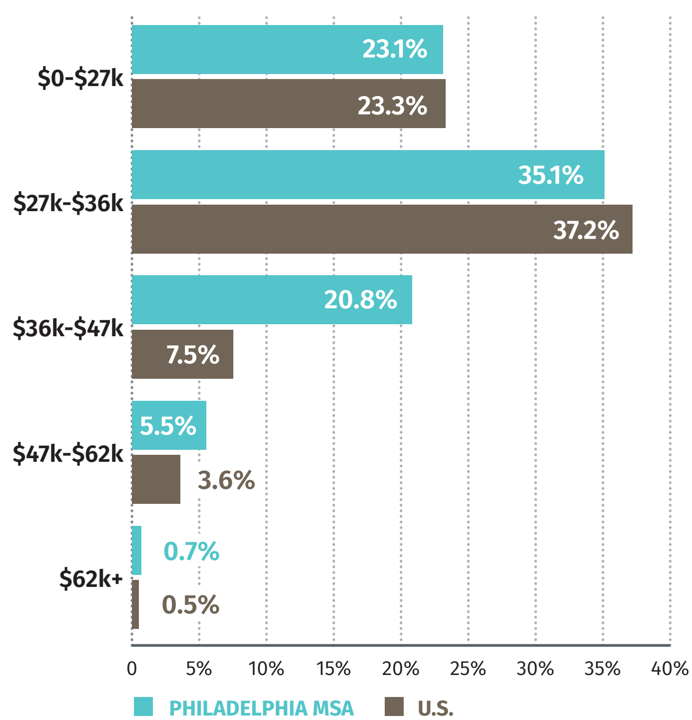
FIGURE 3 SHARE OF HIGH-RISK JOBS, BY EDUCATIONAL REQUIREMENT



Notes. High-skill jobs require a bachelor's degree or higher; middle-skill jobs require a postsecondary nondegree credential, some college, or an associate's degree; low-skill jobs require a high school diploma or less.

Sources: Authors' calculation based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

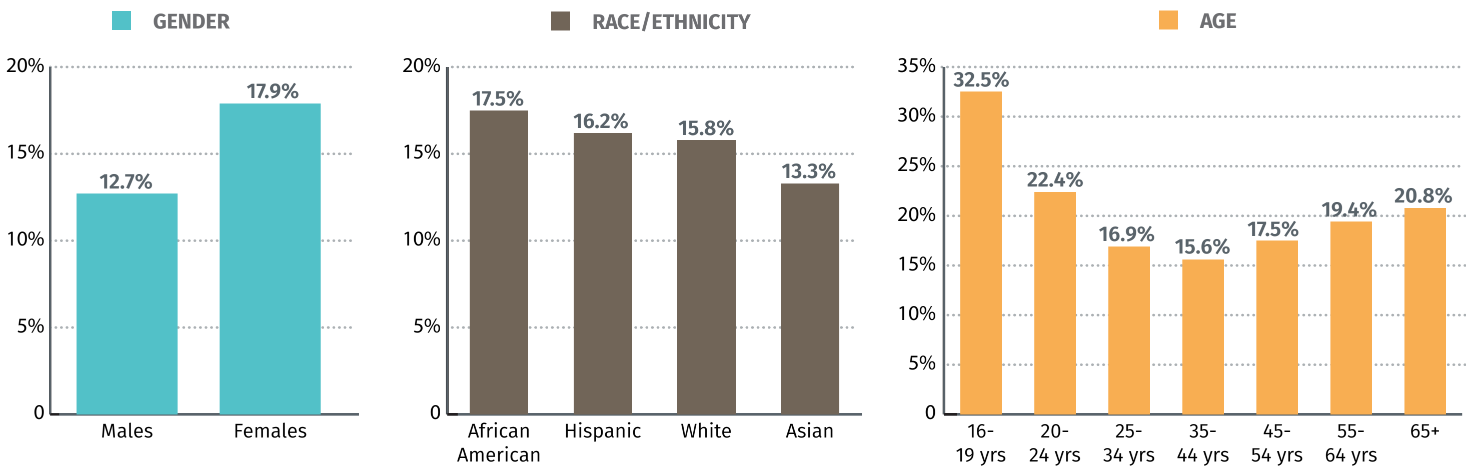
FIGURE 4 SHARE OF HIGH-RISK JOBS, BY ANNUAL MEDIAN WAGE



Notes. Area median wages have been adjusted with regional price parities data to ensure wages are comparable across different MSAs.

Sources: Authors' calculation based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

FIGURE 5 SHARES OF JOBS WITH A HIGH RISK OF AUTOMATION BY GENDER, RACE/ETHNICITY, AND AGE, PHILADELPHIA MSA



Notes. Data were aggregated to calculate gender shares and race/ethnicity shares, respectively, using American Community Survey data.

Sources: Authors' calculation based on data from Frey and Osborne (2017), 2016 American Community Survey, and Bureau of Labor Statistics (2016)

Female, Minority, Younger, and Certain Older Workers Hold Disproportionately Larger Shares of Jobs at High Risk of Automation

As Figure 5 shows, for high-risk occupations, women will be more directly affected by having their jobs automated across all MSAs than men. On average, about 13.8 percent of jobs held by men in all MSAs are at a high risk of automation, compared with 19.7 percent for women.[5] In the Philadelphia MSA, while 17.9 percent of jobs held by women are at a high risk of automation, 12.7 percent of jobs held by men are.

In general, black or African American and Hispanic or Latino workers are more likely to be affected by job automation than non-Hispanic whites and Asians. Across all MSAs, about 18.2 percent of occupations held by black or African American workers and 17.5 percent of occupations held by Hispanic or Latino workers are at a high risk of automation. In the Philadelphia MSA, about 17.5 percent of jobs are at a high risk of automation for black or African Americans, higher than the 16.2 percent for Hispanic or Latino workers, the 15.8 percent for non-Hispanic whites, and the 13.3 percent for Asians.

Younger workers, primarily ages 16 to 24, hold the most jobs at a high risk of automation across all MSAs. In the Philadelphia MSA, about 32.5 percent of workers ages 16–19 and 22.4 percent of workers ages 20–24 hold high-risk automatable jobs, higher than workers ages 35–44 (15.6 percent). Workers ages 55–64 and 65 and over also see a greater risk of automation than workers ages 35–44 (19.4 percent and 20.8 percent, respectively, versus 15.6 percent in the Philadelphia MSA).

A Recap: Who Will Be Most Impacted By Automation?

An occupation's risk of automation generally declines as educational requirements and wage rates rise. High-risk jobs are highly concentrated among female, minority, younger, and certain older workers, groups that are already in a vulnerable position in the labor market. The burden placed on these workers to compete for the potentially scarce jobs as automation progresses is troubling, as are the disparities between wealthier MSAs and smaller or poorer MSAs with more low-skill and low-wage jobs that can be automated away. Lower-skill, less advantaged workers, as well as some poorer MSAs, are likely to be left behind and need more assistance to avoid exacerbating risks as the adoption of automation progresses.

However, since the adoption of automation is likely to be a slow process for many occupations, there are potential opportunities for enough new jobs to be created for displaced workers. The next section of this report describes where job growth is occurring and how that informs ways to help communities reduce some of the risk for job automation in their local context.

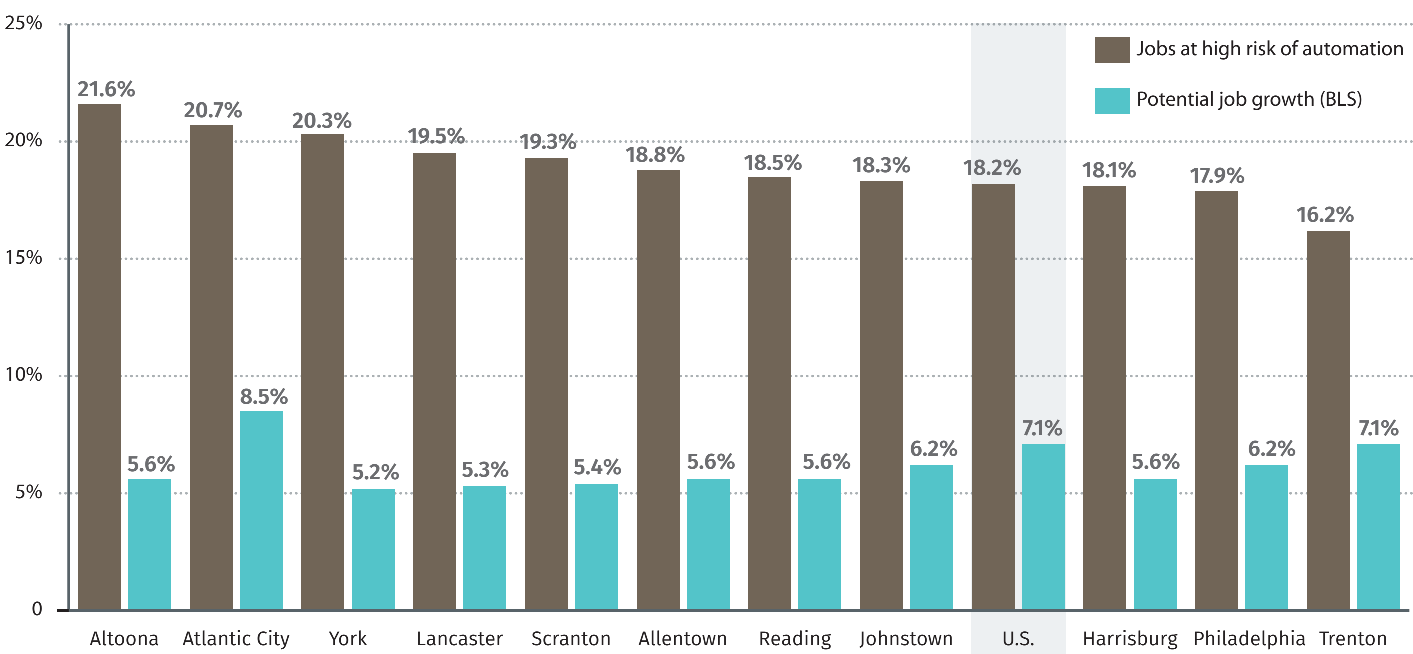
2 TEMPERING THE RISK:
Will We Have Enough New Jobs for Displaced Workers?

With sufficient economic growth, there could be enough new job creation to accommodate the workers displaced by automation. First, the demand for labor could increase as economies grow, even net of jobs replaced by automation. Higher productivity and profits achieved through automation may lead firms to hire additional workers, and higher incomes from improved productivity could generate demand for jobs throughout the economy, such as the increased jobs in the leisure and hospitality sector in the U.S. (Furman and Seamans, 2018). Second, automation creates new jobs to complement tasks taken over by machines. For example, job losses at brick-and-mortar department stores could be more than offset by new opportunities at fulfillment and call centers (Mandel, 2017). There could also be more jobs added in banks' marketing and customer service departments as human teller jobs are replaced by the automatic teller machines (ATMs) (Bessen, 2015). Third, new jobs directly linked to the development, implementation, and maintenance of automation technologies are likely to be in greater demand.

There Could Be Enough New Jobs for Displaced Workers

As we learned from history, neither job growth nor job losses can be easily forecast. Here we attempt to use the national and state-level BLS employment projections for the 2016–2026 period to shed light on the possible job opportunities for displaced workers. Net of job losses in declining sectors, the BLS data project 7.1 percent net job growth in the U.S. from 2016 to 2026, and the growth ranges from 5.2 percent to 8.5 percent for different Third District MSAs (Figure 6). Assuming the labor force remains constant, for the Philadelphia MSA, a simple calculation suggests there could be enough jobs to offset the job losses induced by automation if the adoption rate of automation among high-risk occupations is below about 34.7 percent in the next decade (the net job growth rate of 6.2 percent divided by 17.9 percent of high-risk jobs). To put this in context, for various consumer technologies adopted recently, the time from commercial availability to 80 percent adoption ranges from approximately eight to 28 years (Manyika et al., 2017b), with capital-intensive technologies that require physical installation, like robotics or driverless cars, likely taking even longer. Thus, while one-third or more of high-risk occupations in the Philadelphia MSA could be replaced by automation in the next decade or so, the chance of such a scenario becoming reality may not be very high.

FIGURE 6 SHARE OF HIGH-RISK JOBS AND POTENTIAL JOB GROWTH, THIRD DISTRICT MSAs AND U.S.

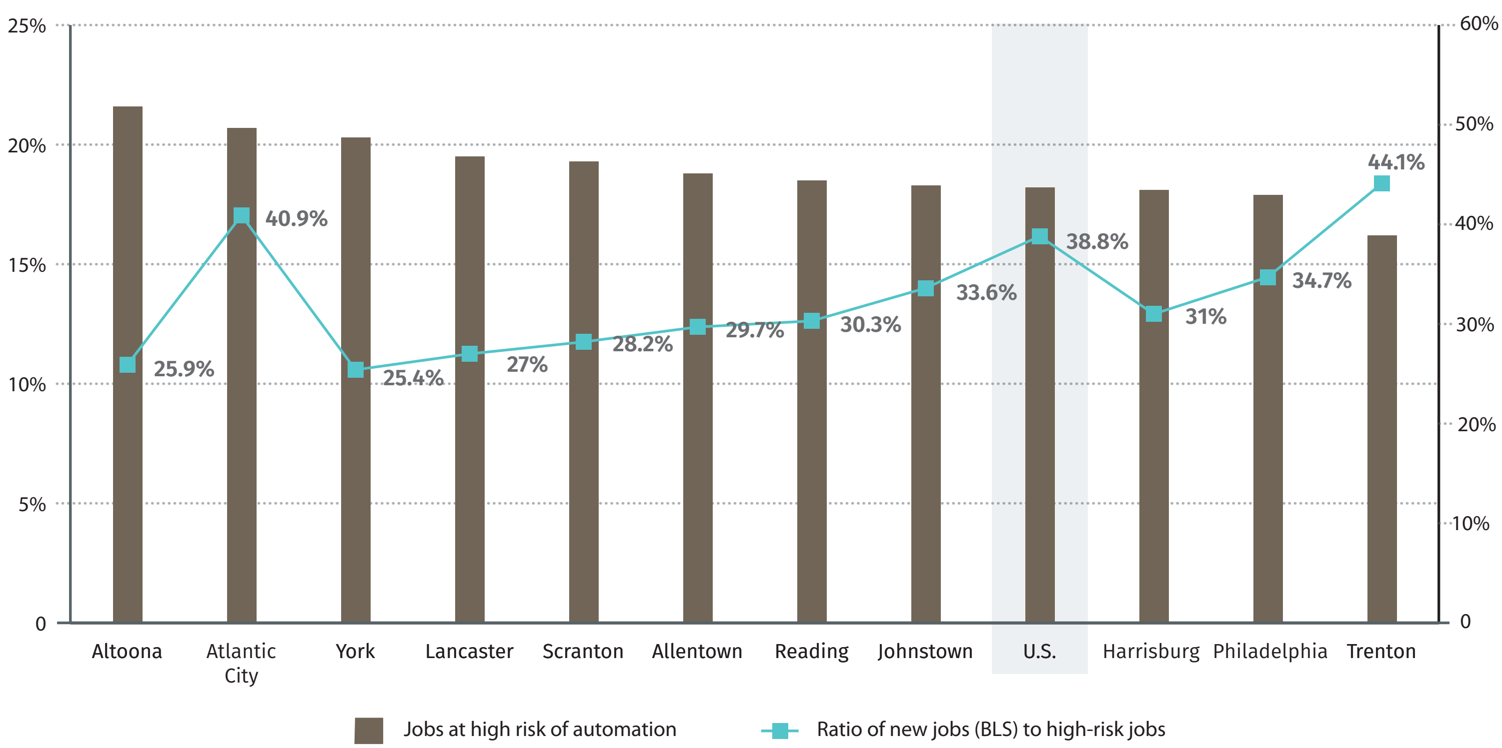


Sources: Authors' calculations based on data from Frey and Osborne (2017), Manyika et al. (2017b), and Bureau of Labor Statistics (2016)

The value of the ratio of new jobs to high-risk jobs, or the breakeven adoption rate, could shed light on the chance of success for individual MSAs in this workforce transition. A larger ratio generally indicates there will be more job opportunities for displaced workers and that the chance of net job losses will be lower. This ratio varies significantly across MSAs in the Third District, ranging from 25.4 percent in York to 44.1 percent in Trenton (Figure 7). In general, displaced workers in bigger and relatively wealthier metros, like the Philadelphia and Trenton MSAs, have a greater chance of securing new jobs because these areas have more new jobs and relatively fewer workers likely to be replaced by automation. However, these same MSAs (Philadelphia and Trenton) are more likely to experience a faster adoption rate because they have higher wages (Figure 8) and likely greater levels of innovation. Their relatively stronger economic and productivity growth and innovation capacity could increase the pace of automation adoption while generating new labor demand. As a result, workers in high-risk jobs in these areas could be replaced earlier than those in relatively poorer areas, while the higher levels of high-risk jobs in smaller and low-wage areas could be less threatened because of relatively slower adoption rates.

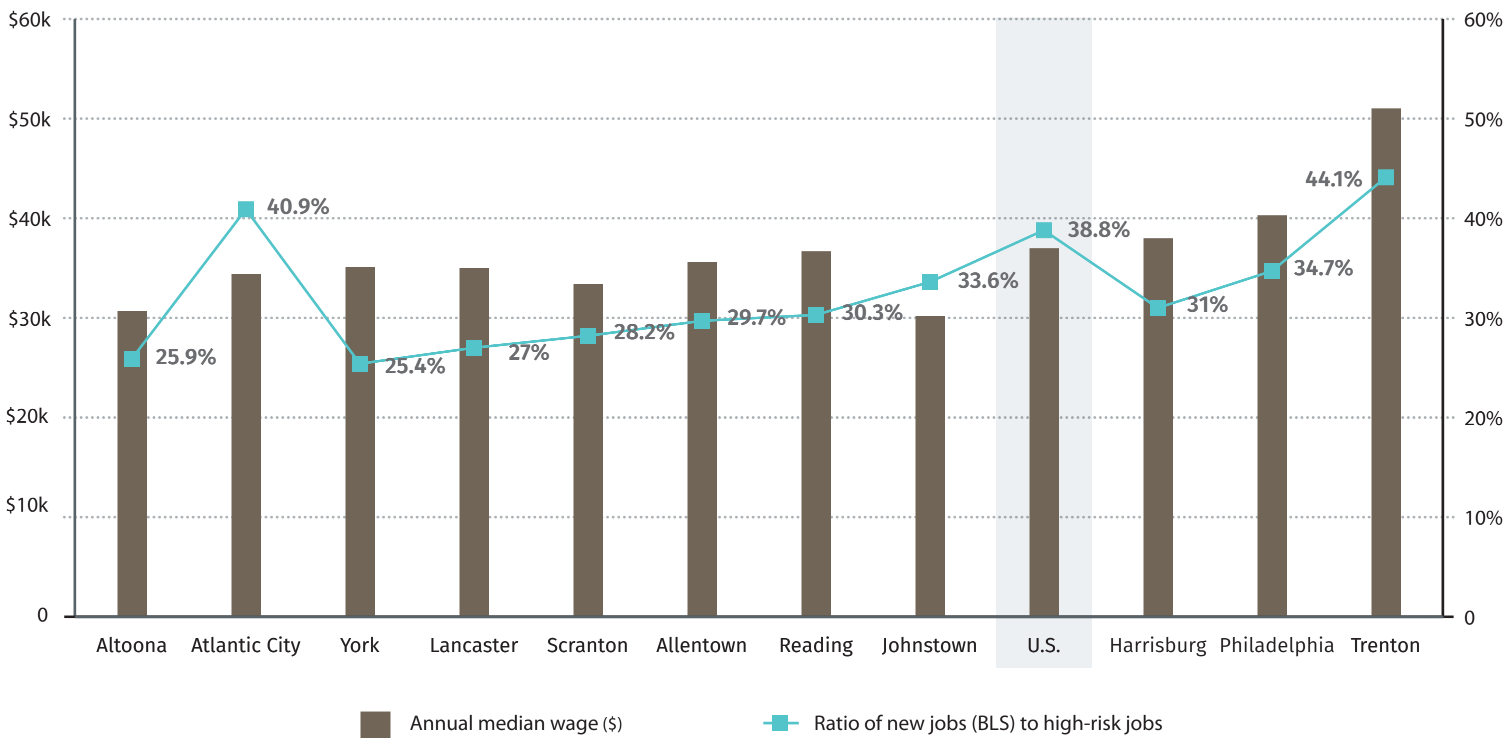
Of course, there could be job losses in certain time periods or in certain areas. First, projections of future employment growth are based on national or state-level data, which do not necessarily take into consideration factors influencing labor demand in particular MSAs. The projected job growth may not be distributed evenly, and if they are spatially concentrated in certain major MSAs, there will be fewer job opportunities than predicted for displaced workers in other areas. For example, Diamond (2016) finds there are more skilled job opportunities in cities that had relatively skilled populations in 1980, such as the San Francisco or Boston areas, than in cities that were relatively less skilled. Furthermore, rapid adoption of individual technologies may lead to significant job losses for workers in particular occupations. Displaced workers may also need time to find new work, and this slowed reemployment process could lead to higher frictional unemployment in the short run.

FIGURE 7 SHARE OF JOBS WITH A HIGH RISK OF AUTOMATION AND RATIOS OF NEW JOBS (BLS) TO HIGH-RISK JOBS, THIRD DISTRICT MSAs AND U.S.



Sources: Authors' calculation based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

FIGURE 8 ANNUAL MEDIAN WAGE AND RATIO OF NEW JOBS (BLS) TO HIGH-RISK JOBS, THIRD DISTRICT MSAs AND U.S.



Notes. Area annual median wages are not adjusted by area living costs.

Sources: Authors' calculation based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

3 OCCUPATIONS IN TRANSITION:
Connecting At-Risk Workers with Opportunities

Automation could displace lower-skill jobs while creating better-paying ones. Displaced workers thus could switch occupational categories as labor markets adjust to changes in labor demand resulting from automation.

However, because of the skills mismatch between potentially displaced workers and the skills those new job opportunities require, displaced workers will need assistance to develop new skills or obtain higher education credentials either to secure a new job or to switch to an existing low-risk job.

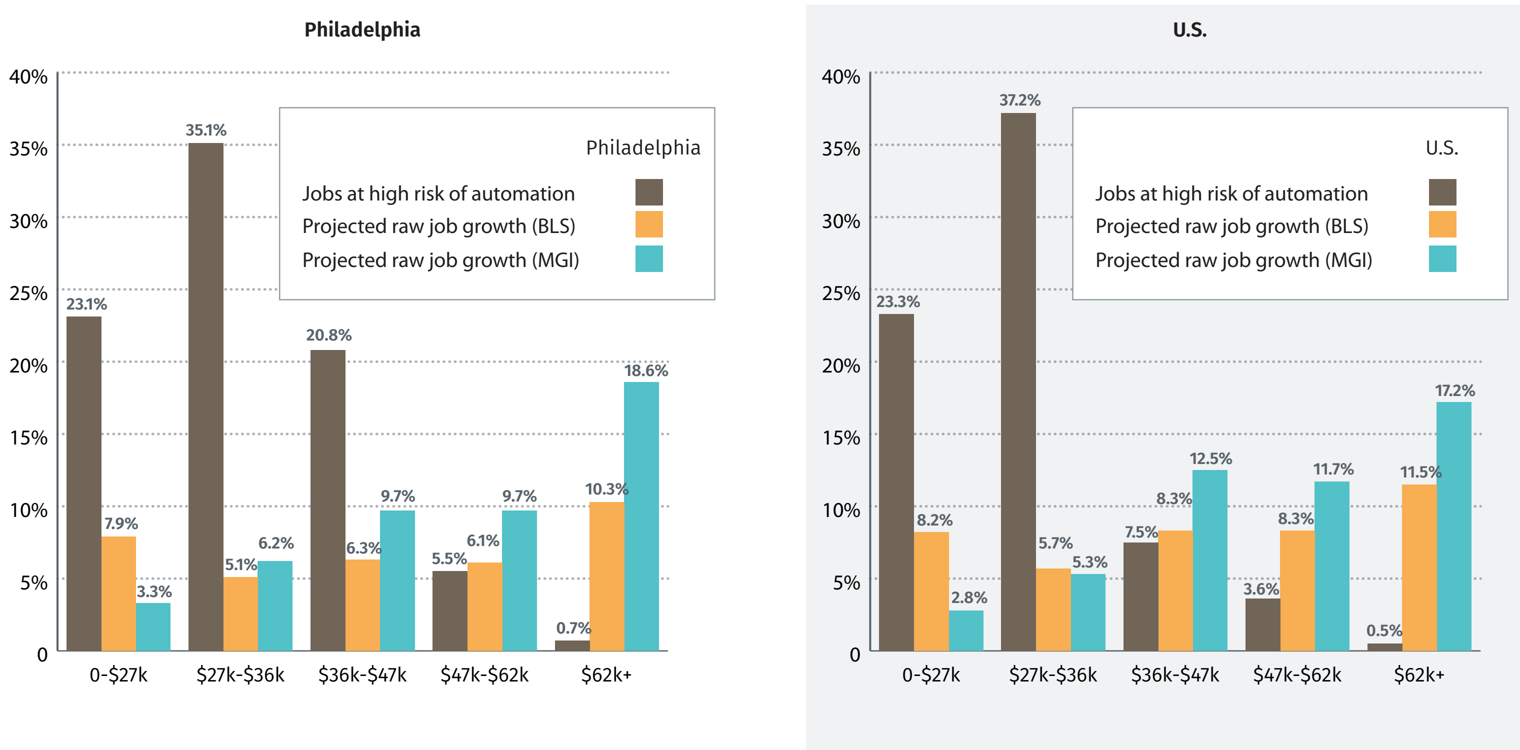
Mismatch in the Quality and Skill Requirements Between New and High-Risk Jobs

We use data from two different sources — the BLS data and the growth sectors identified by the McKinsey Global Institute (MGI) — to evaluate the potential discrepancies in the job quality and skills requirements between jobs at a high risk of automation and new job opportunities. We focus on any new jobs in the growth sectors, all of which might be accessible to displaced workers, instead of net job growth at the aggregate level. Both approaches reach similar levels of job growth in growth occupations (about 8.1 percent of the 2016 employment using the BLS approach and 8.0 percent using the MGI approach), although the sectors identified by each approach are somewhat different.[6] Table A3 in Appendix A lists the top 10 occupations based on the BLS approach in terms of job growth in Third District MSAs.

The unequal distribution of the quality and skill requirements between new and high-risk jobs clearly shows where more assistance is needed to help transition displaced workers. Figure 9 compares the quality, measured by annual median wage, of the occupations that will be in demand with that of high-risk jobs in the U.S. and in the Philadelphia MSA. The pattern is quite obvious: Lower-income jobs, especially those at or below $36,000 per year, are more susceptible to automation; in contrast, occupations with higher wages (above $36,000) expect much higher levels of job growth, and the MGI data suggest an even larger increase for the higher-wage occupations than do the BLS data. In short, new jobs created tend to be higher-wage jobs than those displaced by automation.

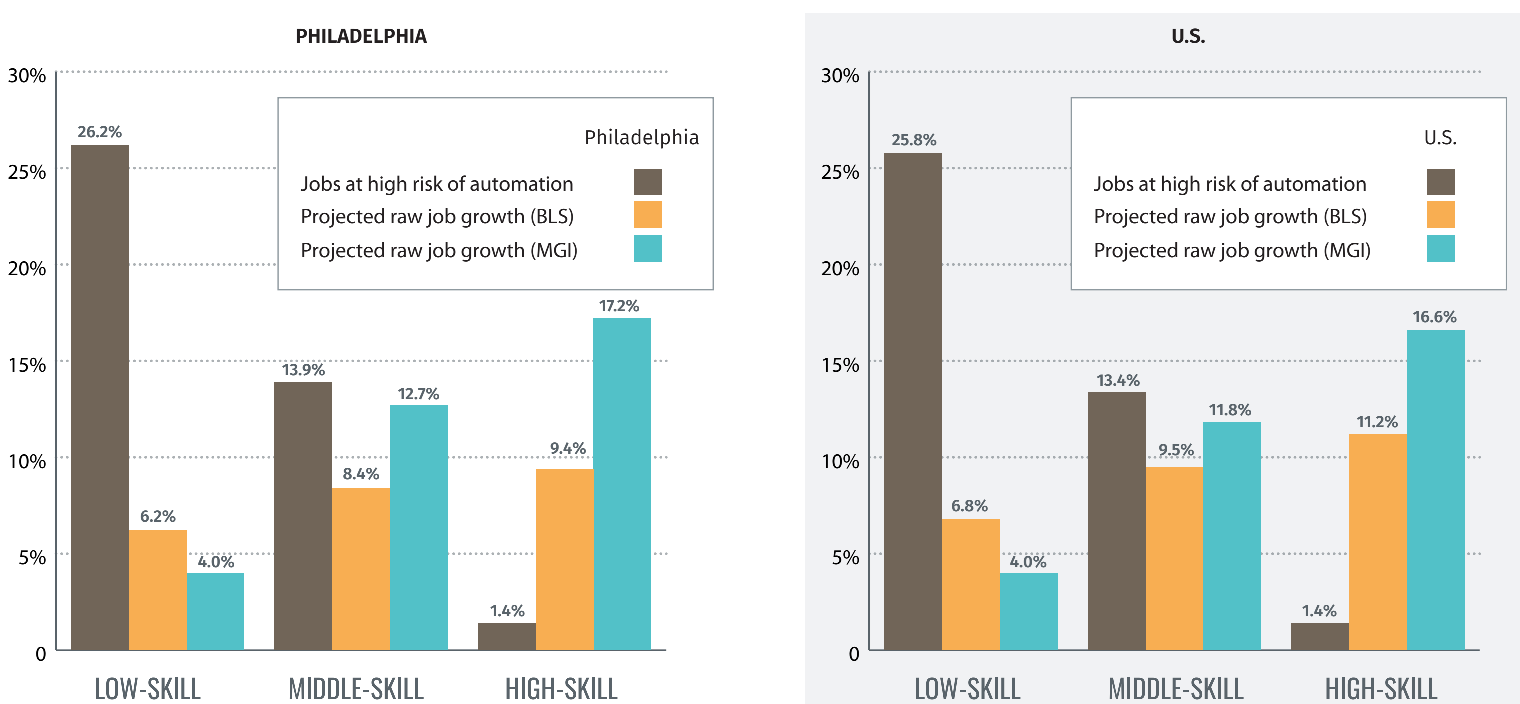
Furthermore, there is a significant mismatch in the skill requirements of the occupations that will be in demand and the jobs at high risk of automation (Figure 10).[7] High-skill occupations — those requiring a bachelor's degree or higher — will see the most growth as a percentage of jobs in the economy. Middle-skill occupations, which require training on top of a traditional postsecondary degree, will see moderate increases, while low-skill occupations, which currently require only a high school diploma or less, have the fewest job opportunities. The skill mismatch documented here is consistent with the pattern of "skill-biased technical change" in the literature (e.g., Violante, 2008), which describes the phenomena that technologies increase the productivity and complement the work of high-skill workers, while machines and robots substitute for many routine tasks that had been undertaken by low-skill workers. If displaced workers, who are disproportionally the low-skill ones, want to take a typical new job, many of them will need to switch occupational categories and learn new skills. This could be challenging for some midcareer workers who cannot afford to spend years earning a traditional degree or who may have significant difficulty in learning new technical skills. This is also a challenge for those who are already in vulnerable positions in the labor market, living paycheck-to-paycheck, with unstable schedules and unpredictable weekly wages.

FIGURE 9 SHARE OF HIGH-RISK JOBS AND PROJECTED JOB GROWTH BY ANNUAL MEDIAN WAGE, PHILADELPHIA MSA AND U.S.



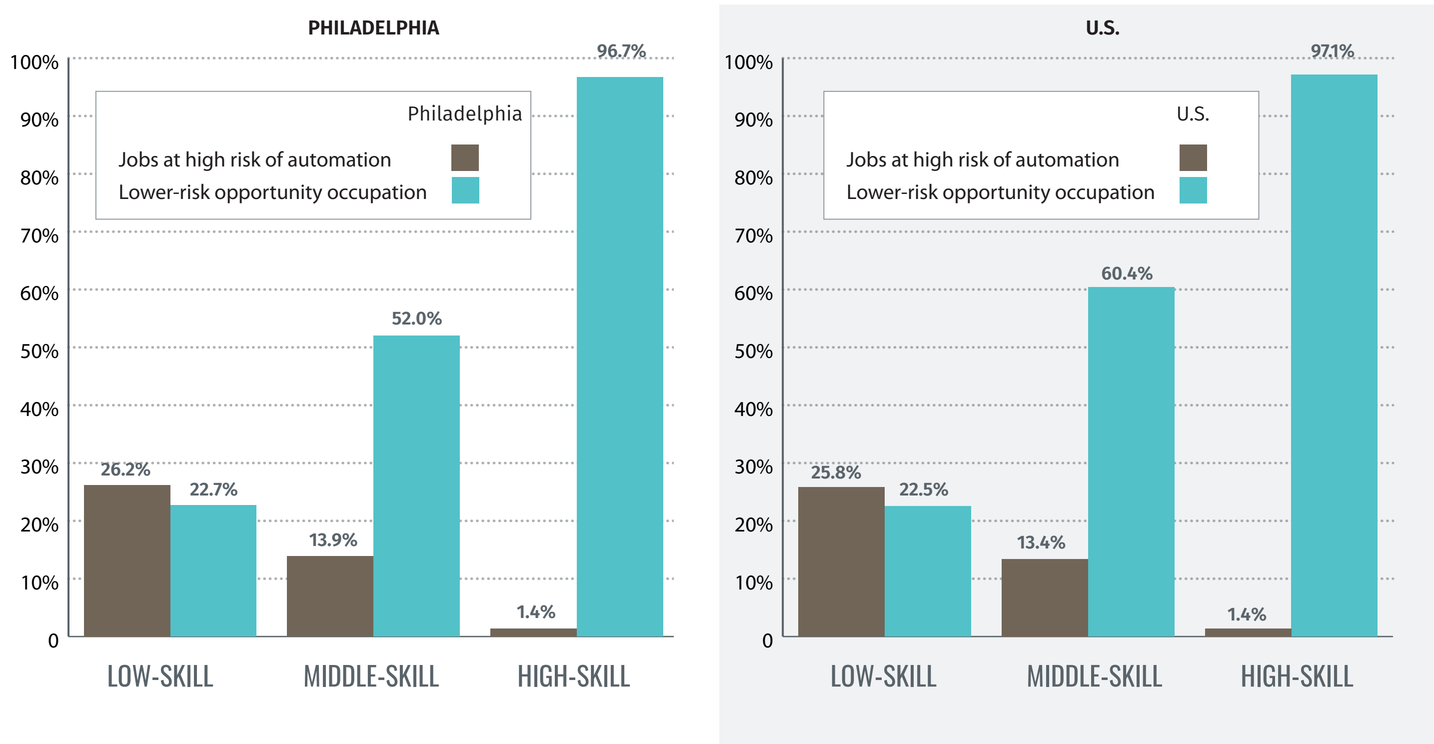
Sources: Authors' calculation based on data from Frey and Osborne (2017), Manyika et al. (2017b), Bureau of Labor Statistics (2016)

FIGURE 10 SHARE OF HIGH-RISK JOBS AND PROJECTED JOB GROWTH BY EDUCATIONAL REQUIREMENT FOR ENTRY-LEVEL JOBS, PHILADELPHIA MSA AND U.S.



Sources: Authors' calculation based on data from Frey and Osborne (2017), Manyika et al. (2017b), and Bureau of Labor Statistics (2016)

FIGURE 11 SHARE OF HIGH-RISK JOBS AND LOWER-RISK QUALITY JOBS BY EDUCATIONAL REQUIREMENT FOR ENTRY-LEVEL JOBS, PHILADELPHIA MSA AND U.S.



Note: Lower-risk quality jobs are defined as non-high-risk jobs (automation probability below 70 percent) that pay at least the national median wage.
Sources: Authors' calculation based on data from Frey and Osborne (2017), Manyika et al. (2017b), Bureau of Labor Statistics (2016), and Federal Reserve Bank of Atlanta "Opportunity Occupation" data

Mismatch in the Skill Requirements Between Low-Risk Quality Jobs and High-Risk Jobs

Displaced workers could also switch to lower-risk occupations, but they also require much higher skills (Figure 11). The educational requirements for occupations that have a lower risk of automation and provide a family-supporting income (i.e., above the national median income after adjusting for cost of living across regions) are much higher than those for the jobs displaced by automation.

Realistically, many displaced workers can take low- or middle-skill jobs freed up by workers with higher skills who are moving up the career ladder. For example, new positions in robotics programming, systems integration, or machine learning in the IT industry are more likely to be taken by experienced computer engineers, while displaced workers will have the opportunity to take lower-skill IT supporting jobs freed up by those workers. In this case, in order to qualify and succeed in their new jobs, all the workers moving up the skill ladder will need to improve their skills.

Related research has identified *opportunity occupations*, jobs requiring low- or middle-skills but with decent pay (Wardrip et al., 2015). As an illustration, Table A4 in the Appendix details the opportunity occupations across Third District MSAs that are also at a lower risk of automation and may be reasonable positions that workers displaced from low-skill, low-pay jobs can transition into.

Connecting At-Risk Workers with Opportunities

Very likely, displaced workers need to consider other postsecondary options or improve their skills in order to switch occupational categories, whether they want to secure a newly created job generated by technology-induced productivity growth or transition to a lower-risk existing job. Existing workers may also need to switch occupations in order to take advantage of new job opportunities. There is no doubt that the coming workforce transitions and the resulting demand for skills upgrades will be significant (Manyika et al., 2017b).

As mentioned earlier, the jobs threatened by automation, however, are not evenly distributed across society. The significant mismatch in the quality and skill requirements between the new and the displaced jobs implies the economic gains may not necessarily benefit those who need the most support. Low-wage, low-skill workers, as well as other less advantaged populations in the labor market, are more likely to find themselves either displaced by new technologies or ill-suited for the new job opportunities. Most of them face the dilemma of having fewer economic resources and time to devote to gain the skills that will become more sought after in the new automation age, such as competitive soft skills (e.g., interpersonal communication or team leadership) and technical skills like programming.

Thus, the major challenge induced by automation is how to connect people whose jobs are likely to disappear because of automation to new job opportunities, rather than the possible job losses alone. Automation could generate more opportunity and growth overall, but we need to make sure the benefits are broadly shared for the economy to continue to proposer. To prepare for the complex workforce transitions ahead, policymakers need to rethink education and workforce development, among other policies, to support those facing a higher risk of being displaced while having fewer resources to help the adjustment. For example, how should we improve educational systems to prepare students for an economy with rapid technological advancements? How should we help connect low-skill and other less advantaged displaced workers to quality occupational opportunities? How can we better leverage skills that displaced workers have, either by training or certification, to help them transition to new jobs? And finally, how can policymakers, corporations, nonprofits, and other stakeholders develop more systematic approaches to address the possible concentrations of automatable jobs in certain occupations and in certain geographic areas?

4 SUMMARY AND IMPLICATIONS

Automation can improve productivity and economic growth but could also disrupt peoples' jobs and lives. Some jobs that have long required human labor will be fully replaced by automation, while other occupations will experience changes in the mix of tasks and activities. The results of this study shed light on how automation could affect future job opportunities across geography and subpopulations. Our analysis suggests that automation could destroy jobs, but automation may not necessarily lead to mass technological unemployment because increased automation could create enough better-paying jobs to mitigate automation's negative employment impact.

Automation-induced job losses may not be a major concern; however, the relatively larger negative impacts of automation on low-skill and less advantaged workers, as well as the variation in its effects across geographic areas, are more worrisome. If the benefits from technology advancements cannot be shared by the less advantaged populations and areas, income inequality is likely to grow, and economic mobility may decrease. The adoption of automation itself with a goal to boost economic growth and improve productivity may be threatened.

Despite the real threat for vulnerable workers, there are still significant technical challenges and other complications preventing the wide adoption of many automation technologies. At the time of writing, the economy is still strong, and there could even be increased demand for some occupations classified as high risk for automation in the near future. By no means should the results of this study be misinterpreted as urging workers in these occupations to switch their jobs now. However, policymakers, companies, other education and training institutions, and individuals need to work together to smooth large-scale workforce transitions in the long term for both those who are at risk of being displaced as well as those who need to adjust to new tasks to keep their jobs. The magnitude of automation's effects on different groups is geographically diverse and will likely require locally designed solutions to address job automation risks.

FOOTNOTES

[1] This simple analysis is for illustration purpose only and assumes the labor force remains constant.

[2] Frey and Osborne (2017) consider occupations having a 70 percent likelihood of automation or greater as having a high-risk for automation and find 47 percent of U.S. employment is highly susceptible to automation. Their study, however, has been criticized for overestimating the share of automatable jobs because of its focus on occupations, instead of individual tasks of the occupation, and for not considering variation between jobs with the same name (e.g., Arntz, et al. 2016).

[3] The pattern of the variation among MSAs has been quite consistent when the alternative automation risk measures (e.g., the shares of at-risk jobs or automatable tasks), are used; the discussion will focus on the high-risk measure hereafter.

[4] Although the metropolitan areas have relatively higher income, the city of Philadelphia and the city of Trenton have much lower income (the suburban areas in the Philadelphia MSA and the Princeton area in the Trenton MSA are much wealthier than the principal cities), so the generally low automation risk in an MSA may not necessarily reflect the challenges for the MSA's principal city or cities.

[5] Census occupational employment data are only available at the two-digit Standard Occupational Classification (SOC) code level by gender and one-digit level by race and ethnicity, so data have been aggregated at various occupational levels. Thus, the results for different gender or racial groups cannot be directly compared with the estimates using occupational-level data (six-digit SOC code), but the comparisons with the reference subpopulation are informative (such as comparisons between women and men or between African Americans and non-Hispanic whites).

[6] The BLS approach, which has a shorter projection period, identifies more low-skill and/or low-wage occupations as growth sectors.

[7] The estimation is based on the educational requirements for entry-level jobs in the BLS 2016 Employment Projections data. The actual skill requirements of new jobs may be different because they rely on management decisions.

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APPENDIX A:

Detailed Data Tables, Third District Metropolitan Statistical Areas (MSAs)

TABLE A1 TOP 10 LARGEST OCCUPATIONS AT A HIGH RISK OF AUTOMATION IN THIRD DISTRICT MSAs

SOC CODE	OCCUPATION	NUMBER OF JOBS	AUTOMATION PROBABILITY
Allentown-Bethlehem-Easton			
41-2011	Cashiers	8,690	97%
43-9061	Office Clerks, General	8,130	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	6,010	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	3,160	98%
51-2092	Team Assemblers	3,080	97%
43-4171	Receptionists and Information Clerks	2,880	96%
35-2014	Cooks, Restaurant	2,640	96%
37-3011	Landscaping and Groundskeeping Workers	2,380	95%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	2,060	98%
51-9111	Packaging and Filling Machine Operators and Tenders	1,980	98%
Altoona			
41-2011	Cashiers	1,990	97%
43-9061	Office Clerks, General	1,610	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	1,200	96%
35-2014	Cooks, Restaurant	640	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	530	98%
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	450	97%
51-2092	Team Assemblers	400	97%
43-4171	Receptionists and Information Clerks	350	96%
43-3021	Billing and Posting Clerks	320	96%
47-2073	Operating Engineers and Other Construction Equipment Operators	260	95%
Atlantic City-Hammonton			
39-3011	Gaming Dealers	4,080	96%
41-2011	Cashiers	3,620	97%
35-2014	Cooks, Restaurant	1,760	96%
43-9061	Office Clerks, General	1,720	96%
43-4171	Receptionists and Information Clerks	1,480	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	1,470	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1,110	98%
37-3011	Landscaping and Groundskeeping Workers	1,020	95%
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	920	97%
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	800	96%
Harrisburg-Carlisle			
43-9061	Office Clerks, General	7,840	96%
41-2011	Cashiers	7,660	97%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	5,560	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	3,190	98%
35-2014	Cooks, Restaurant	2,450	96%
43-4171	Receptionists and Information Clerks	2,190	96%
13-1031	Claims Adjusters, Examiners, and Investigators	1,700	98%
43-9041	Insurance Claims and Policy Processing Clerks	1,580	98%
43-3071	Tellers	1,500	98%
51-2092	Team Assemblers	1,460	97%
Johnstown			
41-2011	Cashiers	1,590	97%
43-9061	Office Clerks, General	1,560	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	1,140	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	530	98%
35-2014	Cooks, Restaurant	400	96%
43-3071	Tellers	320	98%
47-2073	Operating Engineers and Other Construction Equipment Operators	300	95%
43-3021	Billing and Posting Clerks	270	96%
37-3011	Landscaping and Groundskeeping Workers	240	95%
43-4171	Receptionists and Information Clerks	210	96%

TABLE A1 TOP 10 LARGEST OCCUPATIONS AT A HIGH RISK OF AUTOMATION IN THIRD DISTRICT MSAs *(continued)*

SOC CODE	OCCUPATION	NUMBER OF JOBS	AUTOMATION PROBABILITY
Lancaster			
43-9061	Office Clerks, General	5,650	96%
41-2011	Cashiers	5,270	97%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	4,400	96%
51-2092	Team Assemblers	2,840	97%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	2,560	98%
35-2014	Cooks, Restaurant	2,020	96%
43-4171	Receptionists and Information Clerks	1,960	96%
43-5071	Shipping, Receiving, and Traffic Clerks	1,600	98%
37-3011	Landscaping and Groundskeeping Workers	1,350	95%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	1,270	98%
Philadelphia-Camden-Wilmington			
41-2011	Cashiers	69,930	97%
43-9061	Office Clerks, General	62,660	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	48,210	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	31,000	98%
43-4171	Receptionists and Information Clerks	23,320	96%
35-2014	Cooks, Restaurant	20,770	96%
37-3011	Landscaping and Groundskeeping Workers	17,670	95%
43-3021	Billing and Posting Clerks	13,140	96%
43-5071	Shipping, Receiving, and Traffic Clerks	12,060	98%
43-3071	Tellers	9,650	98%
Reading			
41-2011	Cashiers	4,460	97%
43-9061	Office Clerks, General	4,120	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	2,780	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1,690	98%
37-3011	Landscaping and Groundskeeping Workers	1,570	95%
35-2014	Cooks, Restaurant	1,510	96%
51-2092	Team Assemblers	1,310	97%
43-4171	Receptionists and Information Clerks	1,190	96%
43-5071	Shipping, Receiving, and Traffic Clerks	1,070	98%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	680	98%
Scranton–Wilkes-Barre–Hazleton			
41-2011	Cashiers	7,400	97%
43-9061	Office Clerks, General	6,200	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	4,410	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	2,840	98%
51-2092	Team Assemblers	2,720	97%
35-2014	Cooks, Restaurant	2,300	96%
43-3071	Tellers	1,600	98%
51-9111	Packaging and Filling Machine Operators and Tenders	1,550	98%
37-3011	Landscaping and Groundskeeping Workers	1,450	95%
43-5071	Shipping, Receiving, and Traffic Clerks	1,310	98%
Trenton			
41-2011	Cashiers	4,830	97%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	4,370	96%
43-9061	Office Clerks, General	3,880	96%
43-4171	Receptionists and Information Clerks	2,600	96%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	2,400	98%
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	1,670	96%
43-5071	Shipping, Receiving, and Traffic Clerks	1,390	98%
37-3011	Landscaping and Groundskeeping Workers	1,360	95%
35-2014	Cooks, Restaurant	970	96%
43-9041	Insurance Claims and Policy Processing Clerks	900	98%
York-Hanover			
41-2011	Cashiers	5,600	97%
43-9061	Office Clerks, General	3,810	96%
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	2,910	96%
51-2092	Team Assemblers	2,770	97%
43-3031	Bookkeeping, Accounting, and Auditing Clerks	1,600	98%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	1,400	98%
35-2014	Cooks, Restaurant	1,350	96%
43-4171	Receptionists and Information Clerks	1,210	96%
43-5071	Shipping, Receiving, and Traffic Clerks	1,110	98%
53-3031	Driver/Sales Workers	960	98%

Source: Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

TABLE A2 SHARE OF JOBS AT RISK OF AUTOMATION AND PROJECTED JOB GROWTH IN THIRD DISTRICT MSAs

Job At Risk of Automation	Share of Jobs by Risk of Automation			Share of Jobs at a High Risk by Skill Requirement			Share of Jobs at a High Risk by Median Annual Wage				
	Share of High-Risk Jobs (≥95%)	Share of At-Risk Jobs (70-94%)	Share of Low-Risk Jobs (<70%)	Low-Skill	Middle-Skill	High-Skill	$0–27,000	$27,001–36,000	$36,001–47,000	$47,001–62,000	$62,000+
Allentown	18.8%	33.3%	48.0%	26.1%	9.9%	0.6%	20.4%	42.3%	8.9%	1.6%	0.1%
Altoona	21.6%	33.1%	45.3%	28.1%	11.0%	1.0%	24.1%	45.5%	6.4%	3.9%	0.0%
Atlantic City	20.7%	32.2%	47.1%	26.8%	14.9%	0.9%	19.1%	57.2%	5.1%	1.8%	1.6%
Harrisburg	18.1%	31.3%	50.7%	26.0%	12.0%	1.5%	25.6%	32.7%	8.8%	4.2%	0.3%
Johnstown	18.3%	33.3%	48.5%	24.3%	11.6%	1.3%	17.6%	40.9%	13.6%	3.0%	0.0%
Lancaster	19.5%	35.3%	45.2%	25.2%	12.0%	1.6%	18.3%	45.0%	4.8%	3.1%	0.3%
Philadelphia	17.9%	28.9%	53.2%	26.2%	13.9%	1.4%	23.1%	35.1%	20.8%	5.5%	0.7%
Reading	18.5%	34.0%	47.5%	24.6%	11.7%	0.9%	25.4%	30.4%	16.0%	1.3%	3.2%
Scranton	19.3%	34.0%	46.8%	25.3%	12.8%	1.2%	26.3%	32.2%	6.4%	3.3%	0.0%
Trenton	16.2%	24.3%	59.5%	26.9%	15.7%	1.1%	24.2%	28.3%	38.1%	1.8%	0.6%
York	20.3%	34.5%	45.2%	27.1%	9.9%	0.2%	24.9%	38.7%	9.3%	1.7%	0.0%
U.S.	18.2%	30.4%	51.3%	25.8%	13.4%	1.4%	23.3%	37.2%	7.5%	3.6%	0.5%

Projected Job Growth	Net and Raw Job Growth			Raw Job Growth (BLS) by Skill Requirement			Job Growth (BLS) by Median Annual Wage				
	Net Job Growth (BLS)	Raw Job Growth (BLS)	Raw Job Growth (MGI)	Low-Skill	Middle-Skill	High-Skill	$0–27,000	$27,001–36,000	$36,001–47,000	$47,001–62,000	$62,000+
Allentown	5.6%	6.8%	7.6%	5.7%	8.7%	9.3%	7.2%	4.5%	7.2%	7.1%	9.9%
Altoona	5.6%	6.6%	7.6%	5.6%	8.7%	9.7%	6.8%	4.7%	6.3%	6.0%	11.4%
Atlantic City	8.5%	9.1%	7.0%	9.2%	10.6%	8.3%	10.2%	8.5%	7.0%	6.3%	9.7%
Harrisburg	5.6%	6.8%	8.1%	5.6%	8.4%	9.2%	6.7%	5.4%	7.4%	6.9%	9.6%
Johnstown	6.2%	7.1%	8.1%	6.2%	8.8%	9.8%	7.4%	5.4%	6.9%	5.8%	11.9%
Lancaster	5.3%	6.5%	7.5%	5.6%	8.1%	9.0%	6.9%	4.5%	6.9%	6.7%	9.5%
Philadelphia	6.2%	7.3%	8.6%	6.2%	8.4%	9.4%	7.9%	5.1%	6.3%	6.1%	10.3%
Reading	5.6%	6.7%	7.2%	5.8%	8.0%	9.1%	6.9%	6.1%	5.7%	6.9%	8.9%
Scranton	5.4%	6.7%	7.2%	5.8%	7.9%	9.4%	6.9%	5.6%	6.5%	6.7%	9.5%
Trenton	7.1%	8.3%	9.4%	7.9%	9.2%	8.9%	10.8%	6.6%	5.1%	6.8%	9.3%
York	5.2%	6.4%	7.1%	5.5%	8.1%	8.8%	6.5%	4.9%	6.8%	6.1%	9.3%
U.S.	7.1%	8.1%	8.0%	6.8%	9.5%	11.2%	8.2%	5.7%	8.3%	8.3%	11.5%

Sources: Authors' calculations based on data from Frey and Osborne (2017), Manyika et al. (2017b), and Bureau of Labor Statistics (2016).

TABLE A3 OCCUPATIONS WITH LARGEST JOB GROWTH IN THIRD DISTRICT MSAs

SOC CODE	OCCUPATION	NUMBER OF JOBS	NUMBER OF NEW JOBS PROJECTED 2016-2026	ANNUAL WAGES ($)	AUTOMATION PROBABILITY
Allentown-Bethlehem-Easton					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	9,870	1,638	16,796	92.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	13,870	1,456	25,977	85.0%
29-1141	Registered Nurses	9,410	1,261	59,478	0.9%
39-9021	Personal Care Aides	5,190	971	20,189	74.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	6,120	526	39,460	79.0%
31-1011	Home Health Aides	1,750	471	20,405	39.0%
31-9092	Medical Assistants	2,100	460	27,354	30.0%
35-3031	Waiters and Waitresses	5,770	427	18,614	94.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	5,110	363	23,735	66.0%
53-7051	Industrial Truck and Tractor Operators	3,700	348	30,855	93.0%
Altoona					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	1,480	246	18,260	92.0%
29-1141	Registered Nurses	1,650	221	63,820	0.9%
39-9021	Personal Care Aides	980	183	19,120	74.0%
31-1011	Home Health Aides	470	126	22,740	39.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	1,160	122	23,180	85.0%
31-9092	Medical Assistants	440	96	26,720	30.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	1,080	93	42,050	79.0%
35-3031	Waiters and Waitresses	1,050	78	20,280	94.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	1,000	71	23,100	66.0%
47-2061	Construction Laborers	600	67	27,500	88.0%
Atlantic City-Hammonton					
35-3031	Waiters and Waitresses	5,470	755	19,912	94.0%
31-1011	Home Health Aides	950	467	20,781	39.0%
29-1141	Registered Nurses	2,990	368	67,746	0.9%
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	1,420	307	17,009	92.0%
41-2031	Retail Salespersons	5,970	281	18,167	92.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	2,520	237	24,561	66.0%
37-2012	Maids and Housekeeping Cleaners	2,180	225	21,465	69.0%
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	1,620	222	19,360	91.0%
35-2021	Food Preparation Workers	1,350	170	18,333	87.0%
21-1093	Social and Human Service Assistants	930	165	28,632	13.0%
Harrisburg-Carlisle					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	8,000	1,328	17,716	92.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	11,440	1,201	27,321	85.0%
29-1141	Registered Nurses	7,320	981	61,945	0.9%
31-1011	Home Health Aides	2,180	586	21,588	39.0%
15-1132	Software Developers, Applications	2,180	578	72,321	4.2%
53-3032	Heavy and Tractor-Trailer Truck Drivers	6,350	546	42,669	79.0%
39-9021	Personal Care Aides	2,620	490	21,457	74.0%
35-3031	Waiters and Waitresses	4,900	363	18,186	94.0%
31-9092	Medical Assistants	1,530	335	28,863	30.0%
53-7051	Industrial Truck and Tractor Operators	3,430	322	28,449	93.0%
Johnstown					
39-9021	Personal Care Aides	1,700	318	22,010	74.0%
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	1,680	279	19,445	92.0%
29-1141	Registered Nurses	1,650	221	67,351	0.9%
31-1011	Home Health Aides	310	83	23,539	39.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	1,130	80	20,188	66.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	680	71	25,979	85.0%
43-6013	Medical Secretaries	400	68	27,571	81.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	760	65	46,942	79.0%
35-3031	Waiters and Waitresses	810	60	19,812	94.0%
31-9092	Medical Assistants	270	59	29,162	30.0%
Lancaster					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	5,740	953	16,676	92.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	5,990	629	23,799	85.0%
29-1141	Registered Nurses	4,320	579	57,224	0.9%
39-9021	Personal Care Aides	2,840	531	20,502	74.0%
31-1011	Home Health Aides	1,470	395	22,712	39.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	4,560	392	37,014	79.0%

TABLE A3 OCCUPATIONS WITH LARGEST JOB GROWTH IN THIRD DISTRICT MSAs *(continued)*

SOC CODE	OCCUPATION	NUMBER OF JOBS	NUMBER OF NEW JOBS PROJECTED 2016-2026	ANNUAL WAGES ($)	AUTOMATION PROBABILITY
Lancaster, continued					
35-3031	Waiters and Waitresses	4,320	320	20,667	94.0%
31-9092	Medical Assistants	1,150	252	27,982	30.0%
47-2031	Carpenters	2,920	234	34,402	72.0%
11-1021	General and Operations Managers	2,790	204	92,795	16.0%
Philadelphia-Camden-Wilmington					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	58,930	9,782	16,255	92.0%
29-1141	Registered Nurses	70,830	9,491	65,441	0.9%
39-9021	Personal Care Aides	38,980	7,289	19,854	74.0%
31-1011	Home Health Aides	24,990	6,722	19,897	39.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	51,220	5,378	24,747	85.0%
15-1132	Software Developers, Applications	17,790	4,714	85,861	4.2%
35-3031	Waiters and Waitresses	44,970	3,328	18,689	94.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	42,220	2,998	23,308	66.0%
31-9092	Medical Assistants	13,020	2,851	28,903	30.0%
13-2011	Accountants and Auditors	29,540	2,540	63,290	94.0%
Reading					
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	6,190	650	31,357	85.0%
31-1011	Home Health Aides	2,320	624	21,508	39.0%
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	3,170	526	17,304	92.0%
29-1141	Registered Nurses	3,670	492	58,831	0.9%
39-9021	Personal Care Aides	1,970	368	21,517	74.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	2,720	234	45,401	79.0%
51-9198	Helpers--Production Workers	1,940	223	33,629	66.0%
35-3031	Waiters and Waitresses	2,930	217	18,822	94.0%
31-9092	Medical Assistants	850	186	27,936	30.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	2,360	168	23,723	66.0%
Scranton–Wilkes-Barre–Hazleton					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	7,450	1,237	17,876	92.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	11,730	1,232	29,095	85.0%
29-1141	Registered Nurses	6,120	820	57,404	0.9%
39-9021	Personal Care Aides	3,100	580	21,839	74.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	5,020	432	42,616	79.0%
31-1011	Home Health Aides	1,470	395	23,825	39.0%
53-7051	Industrial Truck and Tractor Operators	3,580	337	33,776	93.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	4,270	303	23,333	66.0%
35-3031	Waiters and Waitresses	3,860	286	20,265	94.0%
43-6013	Medical Secretaries	1,620	274	34,789	81.0%
Trenton					
15-1132	Software Developers, Applications	4,600	1,035	81,548	4.2%
31-1011	Home Health Aides	1,580	777	19,136	39.0%
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	2,570	555	15,933	92.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	3,690	550	21,646	85.0%
29-1141	Registered Nurses	4,170	513	58,924	0.9%
13-1199	Business Operations Specialists, All Other	6,300	447	59,511	23.0%
35-3031	Waiters and Waitresses	2,900	400	16,055	94.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	3,940	370	21,149	66.0%
39-9021	Personal Care Aides	820	322	19,193	74.0%
41-2031	Retail Salespersons	6,160	290	18,525	0.92%
York-Hanover					
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	5,050	838	17,284	92.0%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	7,720	811	29,032	85.0%
29-1141	Registered Nurses	3,570	478	66,024	0.9%
39-9021	Personal Care Aides	1,850	346	21,147	74.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	3,100	267	41,156	79.0%
31-9092	Medical Assistants	1,030	226	27,782	30.0%
35-3031	Waiters and Waitresses	2,910	215	18,609	94.0%
31-1011	Home Health Aides	780	210	22,754	39.0%
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	2,880	204	20,254	66.0%
47-2061	Construction Laborers	1,490	165	34,258	88.0%

Notes: State-level job growth projections are used to estimate MSA job growth. The pool of occupations was ordered based on the top 10 largest amount of new jobs created for each MSA that are not at a high risk for automation and where there were no missing data. Job growth figures are projections until 2026.

Source: Frey and Osborne (2017) and Bureau of Labor Statistics (2016)

TABLE A4 TOP 10 LARGEST GROWING OPPORTUNITY OCCUPATIONS WITH LOWER RISK OF AUTOMATION (<95%) IN THIRD DISTRICT MSAs

SOC CODE	OPPORTUNITY OCCUPATION	AUTOMATION PROBABILITY
Allentown-Bethlehem-Easton		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
51-1011	First-Line Supervisors of Production and Operating Workers	1.6%
49-3023	Automotive Service Technicians and Mechanics	59.0%
47-2031	Carpenters	72.0%
33-3051	Police and Sheriff's Patrol Officers	9.8%
47-2111	Electricians	15.0%
Altoona		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
53-3033	Light Truck or Delivery Services Drivers	69.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
47-2031	Carpenters	72.0%
49-3023	Automotive Service Technicians and Mechanics	59.0%
51-1011	First-Line Supervisors of Production and Operating Workers	1.6%
35-1012	First-Line Supervisors of Food Preparation and Serving Workers	63.0%
Atlantic City-Hammonton		
49-9071	Maintenance and Repair Workers, General	64.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
47-2061	Construction Laborers	88.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
47-2031	Carpenters	72.0%
47-2111	Electricians	15.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
49-3023	Automotive Service Technicians and Mechanics	59.0%
Harrisburg-Carlisle		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
49-9071	Maintenance and Repair Workers, General	64.0%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
49-3023	Automotive Service Technicians and Mechanics	59.0%
15-1151	Computer User Support Specialists	65.0%
33-3051	Police and Sheriff's Patrol Officers	9.8%
47-2111	Electricians	15.0%
Johnstown		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
21-1093	Social and Human Service Assistants	13.0%
49-9071	Maintenance and Repair Workers, General	64.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
33-3051	Police and Sheriff's Patrol Officers	9.8%
47-2031	Carpenters	72.0%
15-1151	Computer User Support Specialists	65.0%
Lancaster		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
47-2031	Carpenters	72.0%
49-9071	Maintenance and Repair Workers, General	64.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%

TABLE A4 TOP 10 LARGEST GROWING OPPORTUNITY OCCUPATIONS WITH LOWER RISK OF AUTOMATION (<95%) IN THIRD DISTRICT MSAs *(continued)*

SOC CODE	OPPORTUNITY OCCUPATION	AUTOMATION PROBABILITY
Lancaster, continued		
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
51-1011	First-Line Supervisors of Production and Operating Workers	1.6%
49-3023	Automotive Service Technicians and Mechanics	59.0%
53-7051	Industrial Truck and Tractor Operators	93.0%
Philadelphia-Camden-Wilmington		
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
49-9071	Maintenance and Repair Workers, General	64.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
47-2061	Construction Laborers	88.0%
33-3051	Police and Sheriff's Patrol Officers	9.8%
15-1151	Computer User Support Specialists	65.0%
49-3023	Automotive Service Technicians and Mechanics	59.0%
Reading		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
51-9198	Helpers--Production Workers	66.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
51-1011	First-Line Supervisors of Production and Operating Workers	1.6%
53-7051	Industrial Truck and Tractor Operators	93.0%
49-9071	Maintenance and Repair Workers, General	64.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
51-4041	Machinists	65.0%
35-1012	First-Line Supervisors of Food Preparation and Serving Workers	63.0%
Scranton–Wilkes-Barre–Hazleton		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
53-7051	Industrial Truck and Tractor Operators	93.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
49-9071	Maintenance and Repair Workers, General	64.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
47-2061	Construction Laborers	88.0%
43-6013	Medical Secretaries	81.0%
33-3051	Police and Sheriff's Patrol Officers	9.8%
Trenton		
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
49-9071	Maintenance and Repair Workers, General	64.0%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
35-1012	First-Line Supervisors of Food Preparation and Serving Workers	63.0%
15-1151	Computer User Support Specialists	65.0%
25-3021	Self-Enrichment Education Teachers	13.0%
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers	0.3%
York-Hanover		
53-3032	Heavy and Tractor-Trailer Truck Drivers	79.0%
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	85.0%
49-9071	Maintenance and Repair Workers, General	64.0%
41-1011	First-Line Supervisors of Retail Sales Workers	28.0%
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.4%
47-2061	Construction Laborers	88.0%
51-1011	First-Line Supervisors of Production and Operating Workers	1.6%
29-2061	Licensed Practical and Licensed Vocational Nurses	5.8%
47-2031	Carpenters	72.0%
49-3023	Automotive Service Technicians and Mechanics	59.0%

Notes: Opportunity occupations require less than a college education and pay above the national median annual income. Occupations are ordered based on the number of jobs in each MSA that are not at a high risk for automation, are projected to grow, and where there were no missing data.
Sources: Frey and Osborne (2017), Federal Reserve Bank of Atlanta, and Wardrip et al. (2015)

APPENDIX B:
Data and Methods

This study primarily uses publicly available Occupational Employment Statistics (OES) data and economic projection data from the Bureau of Labor Statistics (BLS), 2016 five-year estimate American Community Survey (ACS) data from the U.S. Census Bureau, job growth data provided by the McKinsey Global Institute (Manyika et al., 2017b), as well as opportunity occupation data provided by the Federal Reserve Bank of Atlanta (Wardrip et al., 2015). A complete list of data sources used in this study can be found in Table B1.

Estimation of Jobs at Risk of Automation

We define whether an occupation falls into a particular automation risk category based on data from Frey and Osborne (2017): Jobs with 95 percent risk or greater of being automated are defined as *high risk*, those with 70–94 percent risk are defined as *at risk*, while those with less than a 70 percent risk are designated as *low risk*. Automation probabilities are not available for a small share of detailed occupations, and in some cases, an occupation's automation probability is reported at different levels of Standard Occupational Classification (SOC) code (e.g., the five-digit level), instead of the detailed occupation classification (the six-digit level) used in the OES data. In these cases, we hand-selected a small number of occupations and their automation probabilities that closely matched in content with occupations without automation probabilities and imputed the automation probability value for those without the data (imputed automation probability data will be available upon request). When an imputation would require choosing from multiple kinds of occupations and where large differences existed among automation probabilities for those choices, data were not imputed.

We also use the 2016 OES data to estimate shares of jobs at different risk levels within median annual wage categories, approximately based on quintile distributions for the MSA or national level and also adjusted using U.S. Bureau of Economic Analysis regional price parities data to ensure wages are comparable across different MSAs.

Demographic Estimates

The job automation risks for different demographic groups are also examined: by educational requirement, age, race/ethnicity, and gender. We use the BLS 2016 Employment Projections data to link the typical level of education needed for entry-level jobs of an occupation with its risk to automation. By using the data at the national level, we assume that the entry-level requirement for each occupation is the same across all MSAs in this study.[1] For age distributions, we use the 2016 Labor Force Statistics from the Current Population Survey Data.[2]

To obtain estimates of the total number of individuals within occupations by race/ethnicity and by gender with jobs at risk of automation, we use the 2016 ACS five-year estimates, which provide occupational employment data by race, gender, and ethnicity.

Unfortunately, the occupational employment data is only available at two-digit SOC code level by gender and one-digit level by race and ethnicity. Occupations had to be recategorized into these groups. We first estimate the share of high-risk jobs for occupational groups at the one- or two-digit level and then use the share to estimate the risk for workers of different gender or race and ethnicity, based on different demographic composition of individual areas. Because of the aggregation at various occupational levels, these ratios cannot be compared with the numbers estimated using data at the detailed occupation level (the six-digit SOC code), although the relative comparison with the reference subpopulation is informative (such as comparisons between women and men or between African Americans and non-Hispanic whites).

[1] Specifically, the data we use are the "Education and training assignments by detailed occupation" estimates at the national level for 2016, available at https://www.bls.gov/emp/tables/education-and-training-by-occupation.htm. Of course, the entry-level requirement is likely to be different from the educational attainment distribution of existing workers in the occupation (workers may hold more advanced degrees than the entry-level requirement). However, the pattern has been quite consistent when we use the education data for existing workers.

[2] Without data at the MSA level, this provides a proxy for how automation may affect different age groups, although this approach assumes that the age distributions are the same across different MSAs. These data come from Table 11b, "Characteristics of the Employed," available at https://www.bls.gov/cps/cps_aa2016.htm.

Job Growth Estimates

To estimate employment growth among MSAs, we primarily use the national and state-level job growth projections for 2016–2026 compiled by the BLS and the Projections Managing Partnership. The BLS provides data on projected employment by occupation for the nation as a whole, while individual states prepare projections of occupational employment using input from the BLS national projections. We estimate the job growth for different geographies using the state-level projections. The raw growth rates include new jobs in the growth sectors only, while for the net job growth rates job losses in declining sectors have been subtracted from the job growth. For MSAs that cross multiple states (e.g., Philadelphia), we first estimate the job growth using growth rates of individual states and then aggregate the data at the MSA level.

As a robustness check, we also used the raw job growth data with the types of growth sectors that will be in demand in the U.S. through 2030 from a McKinsey Global Institute (MGI) report, *Jobs Lost, Jobs Gained: Workforce Transitions in A Time of Automation* (Manyika et al., 2017b). We take the projected job growth rate for eight occupation groups and match them to the detailed occupations in our BLS occupational employment data set within the same family of occupations (the matching algorithm will be available upon request).

Compared with the MGI approach, the BLS approach identified more low-skill and/or low-salary occupations as growth sectors in Pennsylvania, such as for retail salespersons; food preparation workers; police, fire, and ambulance dispatchers; security guards; receptionists and information clerks; and restaurant cooks. While magnitudes for job growth should be interpreted with caution, the similar trends found based on both methods of assessing job growth provide robustness checks for observed patterns that exist.

Other Data Sets Used

Finally, we used data on opportunity occupations shared by the Federal Reserve Bank of Atlanta behind its public-use data tool: https://www.frbatlanta.org/cweo/data-tools/opportunity-occupations-monitor. Opportunity occupations are defined as jobs that generally require less than a four-year college degree and pay at least the national median wage, adjusted for cost of living differences.

TABLE B1 DATA SOURCES

DATA	SOURCE	LEVEL OF ANALYSIS	LINK
Automation probability of occupation	Frey and Osborne (2017)	Occupation-level, national	Adapted from manuscript
Occupational employment and annual median wage	May 2016 Bureau of Labor Statistics: Occupational Employment Statistics	Occupation-level, MSA; Occupation-level, national	https://www.bls.gov/oes/tables.htm
Educational requirement by occupation	2016 Bureau of Labor Statistics: Employment Projections	Occupation-level, national	https://www.bls.gov/emp/tables/education-and-training-by-occupation.htm
Employment by gender/occupation group	2012–2016 American Community Survey	MSA, national	https://www.census.gov/programs-surveys/acs/data.html
Employment by race/ethnicity/occupation group	2012–2016 American Community Survey	MSA, national	https://www.census.gov/programs-surveys/acs/data.html
Employment by age/occupation	2016 Bureau of Labor Statistics: Labor Force Statistics from the Current Population Survey	Occupation-level, national	https://www.bls.gov/cps/cps_aa2016.htm
Job growth	1) Projections Managing Partnership - Projections Central (BLS)	Occupation-level, state; Occupation-level, national	http://www.projectionscentral.com/Projections/LongTerm
	2) McKinsey Global Institute (MGI)	Occupation group-level, national	https://www.mckinsey.com/mgi/overview/2017-in-review/automation-and-the-future-of-work/jobs-lost-jobs-gained-workforce-transitions-in-a-time-of-automation
Opportunity occupations	Federal Reserve Bank of Atlanta opportunity occupations data	Occupation-level, MSA; Occupation-level, national	https://www.frbatlanta.org/cweo/data-tools/opportunity-occupations-monitor

Federal Reserve Bank of Philadelphia