“Forced Automation” by COVID-19? Early Trends from Current Population Survey Data

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Abstract

This empirical study evaluates whether COVID-19 and the threat of future pandemics has expedited the process of automation in the U.S. The results suggest that the pandemic displaced more workers in automatable occupations, putting them at a greater risk of being permanently automated. The automatable jobs that are more vulnerable to the pandemic include jobs that do not permit remote work, have a high risk of COVID-19 transmission, or are in the most affected sectors. While most of the job losses during the pandemic are expected to be temporary, a replication of the analysis for the Great Recession suggests the losses of automatable jobs could become permanent during the recovery. The pandemic also hit automatable jobs held by minority workers particularly hard, increasing the risk of permanent job losses for these workers who are already vulnerable in the job market.

Keywords: employment, COVID-19, automation

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1. Introduction

Anecdotal evidence from news stories suggests the COVID-19 pandemic has accelerated the pace of automation and exacerbated automation's impact on job losses. The Pennsylvania Turnpike Commission, for example, decided to permanently lay off 500 toll collectors in June 2020 after initially converting its interstate network to a cashless system in response to COVID-19.[2] Similar examples can be found in companies where human customer service agents in call centers were replaced by Watson Assistant, a conversational AI platform,[3] in hotels where human workers were replaced by self-check-in kiosks and cleaning and delivery robots,[4] and in meatpacking factories, where slaughterhouse robots were adopted to prevent workers from getting infected.[5] This study provides the first empirical analysis to date on whether and how COVID-19 has accelerated automation at the aggregate level using nationally representative data from the monthly Current Population Survey (CPS) micro data files.

We contend that COVID-19 accelerates the process of automation through three primary channels. First, as our data show, the pandemic-induced massive layoffs hit automatable jobs, especially those in the service sectors, particularly hard, putting those jobs at an elevated risk of being fully automated.[6] As firms struggle to avoid workplace infections of COVID-19 and prevent shutdowns during the crisis, machinery and software, which are not susceptible to the virus, become more attractive options than rehiring the temporarily displaced human workers. This is expected to be more evident in occupations that are more vulnerable to the pandemic, such as those that have a higher risk of virus transmission or do not permit remote work. Such automation could become permanent if the displaced workers can be easily substituted with readily available technologies and if firms are satisfied with the labor-saving technology. The replacement of hotel workers by self-check-in kiosks during the pandemic and the permanent layoff of toll collectors in Pennsylvania would fall into this category. Of course, the adoption of automation could be costly and time-consuming, and the innovations adopted during the pandemic could be temporary if firms find recalling the temporarily laid-off workers is easier and more cost-effective compared with making huge investments in automation.

Second, even if there is an increased demand for certain occupations during the pandemic, the short-term labor shortages caused by lockdown policies and health concerns incentivize firms to use technology to substitute for workers. These substitutions could be temporary arrangements, but the threat of future pandemics could also make such changes permanent. The increased demand for slaughterhouse robots in meatpacking factories, for example, would belong to this category.

Furthermore, the massive layoffs likely reduce the adjustment costs associated with automation, which are often very high during booming times, and make it easier for firms — not necessarily in those hard-hit sectors — to substitute for workers that can be replaced by existing technology.

[2] See www.paturnpike.com/press/2020/20200602154151.htm.
[3] See time.com/5876604/machines-jobs-coronavirus.
[4] See www.usatoday.com/story/travel/hotels/2020/07/27/hotels-using-robots-delivery-cleaning-amid-covid-19-pandemic/5494472002/.
[5] See www.wired.com/story/covid-19-makes-the-case-for-more-meatpacking-robots/.
[6] At the peak of the pandemic, the U.S. shed around 25 million jobs in two months, much more than during the entirety of the Great Recession.

Actually, since the 1980s, almost all employment losses in routine occupations, which are relatively easier to be automated, occurred during recessions (e.g., Autor, 2010; Hershbein and Kahn, 2018; Jaimovich and Siu, 2018). The loss of more automatable jobs during the recessions were largely substituted by technology during the recoveries, leading to "jobless recoveries." Many strategic and long-term adjustments may be already under way, but the pandemic could push firms to act quickly and few sectors would be immune from such a deepening of automation.

The pressure to use automation technology in occupations with temporary labor shortages, together with the increased risk of replacing displaced workers with machines and software as the pandemic drags on, is likely to accelerate automation, or as Autor and Reynolds (2020) termed it, "forced automation." The forced automation during the pandemic may be temporary and limited but could also be more widespread and permanent, depending on how long it takes for the pandemic to be contained and whether the health crisis evolves into a prolonged economic crisis.

Even after the pandemic, the threat of future pandemics and the massive technological transition into the virtual world induced by the pandemic could induce significant shifts in the labor market and provide a catalyst for more automation in the long term. The growth of e-commerce, online education, and telework in this transition, for example, could be permanent.[7] Just imagine that if retailers are satisfied with their experiment of conducting business online during the pandemic and decide to close more brick-and-mortar stores, more retail jobs are likely to be lost in the long run.[8] New jobs created in booming businesses, like Amazon warehouse jobs, are highly automated and are less likely to fully compensate for the job losses at those retailers. Of course, the looming economic crisis and the pandemic-induced demand shocks may disincentivize new investment in automation. However, in a theoretical piece, Leduc and Liu (2020) suggest pandemic-induced job uncertainty is likely to boost automation, even after taking into consideration the possibly reduced aggregate demand.

Instead of predicting the long-term impact of automation, this study focuses on the question whether the forced automation resulting from COVID-19 has become discernable in high-frequency employment data. Were automatable jobs more likely to disappear during the pandemic? What were the primary channels through which the pandemic could accelerate automation? And how do the likely automation-induced job losses vary across different sociodemographic groups? Furthermore, what are the lessons we can learn from the last recession on automation-induced job losses? Answers to these questions have important implications on how to help technology-displaced workers and handle the likely massive job reallocation during the recovery from the COVID-19 crisis.

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[7] For example, Barrero, Bloom, and Davis (2020) estimate that the anticipated share of full working days at home will increase to 16.6 percent of all working days, even when the pandemic ends, and 32 to 42 percent of COVID-induced layoffs will be permanent. However, Bartik et al. (2020) suggest that a vast majority of new unemployment insurance claimants expected to be recalled to their prior jobs during March to May 2020.

[8] *The Economist* reports that American retailers have already laid off or furloughed one-fifth of their workers as of June 2020: www.economist.com/graphic-detail/2020/06/03/american-retailers-have-laid-off-or-furloughed-one-fifth-of-their-workers.

Overall, the results suggest the pandemic has likely accelerated the process of automation by putting more workers holding technologically automatable jobs out of work, although it is still too early to conclude whether the shift is permanent. Our major results show that:

- Automatable occupations, such as hotel desk clerks, shuttle drivers, retail salespersons, and parking attendants were hit harder by the pandemic. As of August 2020, the more automatable occupations lost 4.2 more jobs per 100 than the occupations with a low risk of automation. That is equivalent to 2.6 million precrisis jobs that were exposed to an elevated risk of being permanently automated.
- The pandemic accelerated automation by displacing workers in more automatable occupations that are more vulnerable to the pandemic's effects, such as those that do not permit remote work, have a high risk of COVID-19 transmission, or are in hard-hit sectors.
- Automatable jobs held by minority workers were hit particularly hard by the pandemic, putting these workers who were already vulnerable in the job market at a greater risk of permanent job loss. By August 2020, automatable jobs held by minority workers experienced 5.1 more job losses per 100 jobs than those held by non-Hispanic whites.
- In case the COVID-19 crisis evolves into a prolonged economic crisis, many job losses in automatable occupations could become permanent in the post-pandemic economy, similar to what happened during the recovery from the Great Recession.

The estimations are primarily based on data from the monthly CPS and data provided from one widely cited study by Frey and Osborne (2017), or the FO measure for simplification. We consider occupations with a 70 percent or greater likelihood of being automated as "at risk" or "automatable" occupations.[9] The jobs that can be fully automated were identified by a group of artificial intelligence and machine learning experts in the early 2010s as those that could be replaced by the demonstrated technologies, and the authors then imputed the probability of automation for individual occupations. Some examples of at-risk jobs include shuttle drivers, retail salespersons, parking attendants, cashiers, receptionists, office clerks, waiters and waitresses, and bank tellers; whereas nurses, dentists, carpenters, plumbers, teachers, scientists, lawyers, and engineers are considered low-risk occupations based on this approach. As of January 2020, there were about 91.1 million jobs, or 59.8 percent of all jobs, in the low-risk category and 61.3 million jobs in the at-risk category.[10]

Although, as we show later, the FO measure is a good predictor of job losses in the previous recession, we acknowledge that we are unable to observe actual automation of individual jobs. The FO measure of automation focuses on the technological feasibility of the automation of an occupation, while other socioeconomic and regulatory factors that may influence the actual adoption may not be fully considered. Costs and other barriers of automation, however, have become less important when facing the life-threatening pandemic. Furthermore, as more jobs

[9] Ding, Leigh, and Harker (2018) uses a more conservative approach by considering occupations having a 95 percent likelihood of automation or greater as having a high risk for automation. However, the pandemic is likely to put more occupations at a moderate risk of automation at risk, so we use a slightly broader definition as in Frey and Osborne (2017).

[10] The analysis is based on a data set we created by linking the FO occupational automation risk data to the monthly CPS micro data using several crosswalk files provided by the Census Bureau and the Bureau of Labor Statistics (BLS). More details about the data and methodology can be found in the Data and Methods section in Appendix A.

became automatable because of rapid technological developments in recent years, especially in the area of artificial intelligence, the use of the FO measure developed in early 2010s provides a more conservative estimation of the impact of automation at the aggregate level. To check the robustness of our results, we replicated the analysis using alternative automation measures, such as occupations' routineness (Foote and Ryan, 2015) or exposure to robots (Webb, 2019), which yield generally consistent results.

In the following sections, we first examine the job losses in occupations with different levels of automation risk during the pandemic, at the aggregate level, and by demographic groups, followed by a discussion of the lessons we can learn from the recent recovery after the Great Recession. We conclude with a discussion on the implications of the likely accelerated automation. A full discussion of data and methods used throughout the report as well as more figures and data tables, are compiled in the Appendix.

2. Were Automatable Occupations Hit Harder by COVID-19?

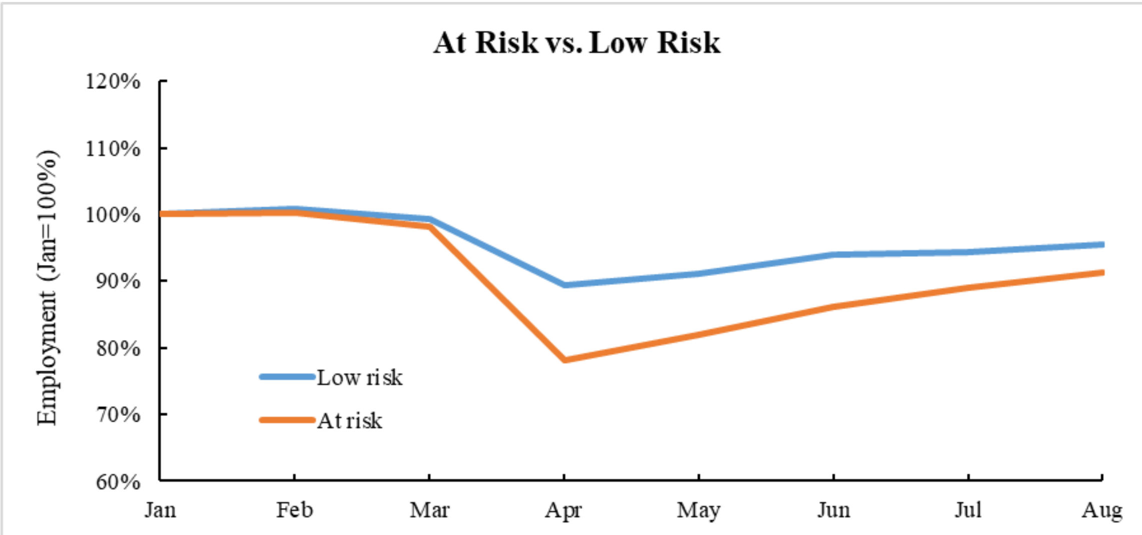
The answer is yes. We find that the pandemic has led significantly larger job losses in occupations at risk of automation, making the substitution of displaced workers by automation much easier. Empirically, we compared the number of jobs in occupations at risk of automation in each month with the precrisis level (the January 2020 level) against the same measure for the control group (occupations with a low risk of automation). To validate the results from the descriptive analysis, we also ran a regression model based on data aggregated at the occupation level.

The pattern is quite obvious. Total employment plummeted from February to April 2020 for both the at-risk and low-risk groups but then started to rebound quickly before the recovery slowed down in June 2020 as the virus resurged. However, by August 2020, more than 40 percent of job losses in April had not been recovered. We observed larger job losses in automatable occupations from January to April 2020 — the month with the most job losses so far — compared with that of the control group (Figure 1, and see more summary statistics in Table A1): a 21.9 percent decline for at-risk occupations versus a decline of 10.6 percent for low-risk ones. Put differently, for every 100 jobs in January 2020, 21.9 jobs in at-risk occupations and 10.6 jobs in low-risk ones were lost by April 2020. A significant portion of job losses in automatable occupations, however, recovered shortly after April. The gap of 11.3 percentage points (21.9 percent minus 10.6 percent) between these two groups shrank to 4.2 percentage points from April to August 2020. Putting this in context, 4.2 percent of jobs in at-risk occupations represented about 2.6 million jobs precrisis.[11] This pattern is generally consistent when alternative automation risk measures were used, although the magnitude of the job loss gap varies (see Figure A1 in Appendix).[12]

[11] See Table A2 in Appendix for a list of major at-risk occupations with the largest decline in employment from January 2020 to August 2020.

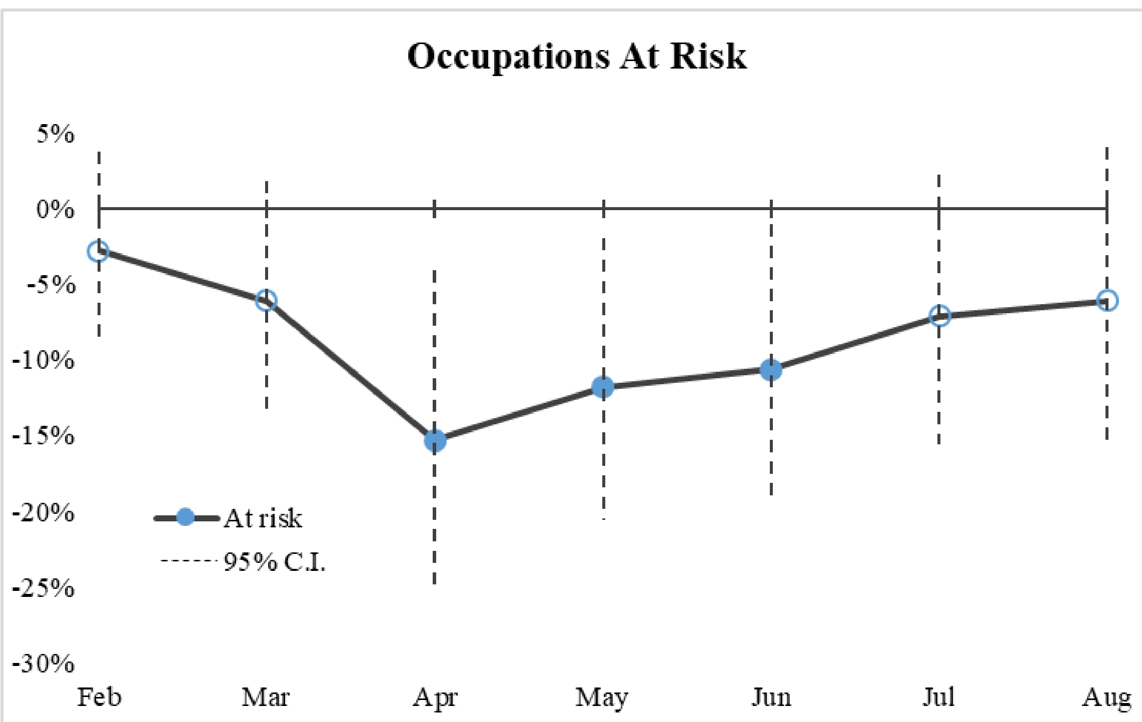
[12] One noticeable difference, however, is that the gap was much smaller between routine jobs, which focus on tasks that can be performed by following a well-defined set of procedures, and nonroutine jobs. This is likely because the COVID-19 crisis has hit many manual nonroutine service jobs, such as cashiers, waiters, and waitresses, harder than others, many of which become technically automatable because of recent technological developments (Frey and Osborne, 2013; Webb, 2019).

Figure 1: Monthly U.S. Employment by Automaton Risk Level in 2020



Sources: Authors' calculation based on data from Frey and Osborne (2017) and the Census Bureau's (2020) Current Population Survey

Figure 2: Regression Estimations of Employment Change by Automation Risk Level, 2020



Note: Markers without filling indicate that the coefficient for that month is not significant at the 5 percent level.
Sources: Authors' calculations based on data from Frey and Osborne (2017) and the Census Bureau's (2020) Current Population Survey

To verify whether the pattern we observed from the descriptive analysis still holds after controlling for job market trends across time and factors specific to individual occupations, we performed a difference-in-differences regression[13] based on data aggregated at the occupation level to assess if the job loss in automatable occupations is significantly larger than that for the control occupations. The regression results confirmed that an occupation with a higher level of automation (at risk) experienced a significantly larger decrease in total employment by April 2020 (15.3 percent larger), but the gap was narrowed to 6.1 percent (and statistically less significant) in August 2020. The quite consistent results from both the descriptive analysis and the occupation-level regression confirm occupations with a higher risk of automation experienced a larger decline in total employment when COVID-19 hit, and many automatable jobs were not recovered several months into the recovery, raising the concern about permanent losses of these jobs that could be replaced by technology.

3. Has COVID-19 Led to "Forced Automation?"

The answer is a tentative yes, although a longer-term and more rigorous evaluation is needed to answer this question more conclusively. The previous section identifies larger job losses in automatable occupations in the first few months of the pandemic. . While some of the losses, such as those for toll collectors and front desk receptionists, could be automated easily and quickly, there could be alternative explanations — other than automation — for the observed losses in other occupations, such as school bus drivers, waiters and waitresses, and gambling services workers. What if the pandemic-induced demand shock was simply higher in industries with a concentration of automatable jobs? What if business shutdown mandates more badly hurt occupations that happen to be more automatable? What if automatable occupations generally are more exposed to viruses and thus were hit hard by COVID-19?

These questions are valid ones. Automatable occupations experienced larger job losses likely partly because they are more vulnerable to the social distancing measures adopted during the pandemic. Thus, we need to compare job loss rates for automatable occupations with jobs with a similar level of susceptibility to the pandemic. The growing literature on the impact of COVID-19 generally agrees that occupations that have a higher risk of virus transmission or do not permit remote work were hit harder by COVID-19 mandates (e.g., Mongey, Pilossoph, and Weinberg, 2020; Montenovo et al., 2020).[14] For example, Angelucci, et al. (2020) find that job losses for nonremote workers were up to three times larger than that of those who can work from home during the pandemic. So we compare the change in total employment in occupations with a similar risk (low or high) of virus transmission (requiring intense physical proximity with customers or coworkers or not) (Mongey, et al., 2020)[15] or in occupations with similar level of

[13] By comparing job losses for an automatable occupation before and during the pandemic, and with occupations with a low risk of automation, the difference-in-differences measures how COVID-19 impacts occupations with different automation risk differently since March 2020, which also can shed light on the effect of automation on individual occupations during the pandemic.
[14] Our own analysis confirms their findings (see Figure A2).
[15] Consistent with the definition in Leibovici et al. (2020), we define an occupation as one with a high risk of virus transmission if the index of occupational contact intensity of an occupation, which is available in the O*NET data, larger than 74.9.

teleworkability (Dingel and Neiman, 2020).[16] The at-risk and low-risk gap for occupations with similar vulnerability to the COVID-19 crisis can thus be more confidently attributed to automation. Similarly, certain sectors, such as leisure and hospitality, personal care, transportation, and retail, were hit harder by COVID-19 than others; thus, we focus on the at-risk and low-risk gap in three sectors with similar levels of demand shock: the hard-hit service sectors,[17] non-hard-hit service sectors, and the nonservice sector.

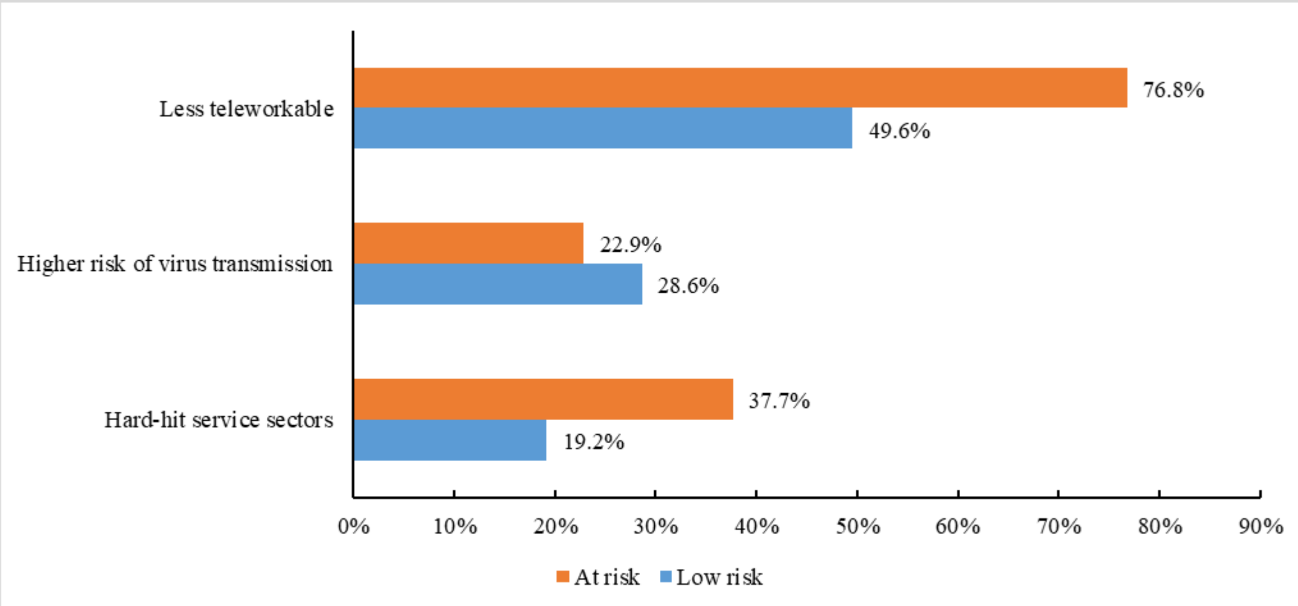
As Figure 3 shows, automatable jobs, on average, are more vulnerable to the pandemic. As of January 2020, more automatable jobs were not teleworkable than the low-risk ones (76.8 percent of at-risk jobs were not teleworkable precrisis, versus 49.6 percent for low-risk occupations) and were more likely to be in hard-hit service sectors (37.7 percent for at-risk jobs, higher than 19.2 percent among low-risk jobs). So, the larger job losses of automatable jobs could be at least partially explained by their larger concentration in less teleworkable occupations and in hard-hit service occupations, which experienced larger job losses during the pandemic. The share of automatable jobs that require extensive physical proximity was slightly lower than that of low-risk jobs; however, many of the low-risk jobs requiring human interactions are either essential workers, such as doctors and nurses, or jobs with better job security, such as school teachers, rather than low-skill service jobs. In short, the results clearly suggest that the uneven shock of the pandemic plays a role in explaining the larger initial job losses, as well as the quicker recovery, in automatable occupations.

We then compare the gap in the rate of job losses between at-risk occupations and low-risk occupations in each group (Figure 4). We use nonremote occupations as an illustration of this comparison: The number of automatable jobs that do not permit remote work experienced a decline of 26.0 percent from January to April 2020, a loss 10.8 percentage points larger than the 15.2 percent decline for those nonremote occupations with a low risk. Put another way, for every 100 at-risk jobs that did not permit remote work in January, 26 of them were lost by April, 10.8 more per 100 than that for low-risk jobs that are also less teleworkable. As of August, the gap was still 5.7 percentage points for occupations that do not allow remote work, higher than the 0.6 percentage point gain for the more teleworkable occupations. The persistent gap in job loss rates between at-risk and low-risk occupations for occupations with similar levels of teleworkability is indicative of a higher risk of permanent losses of the automatable jobs. Similarly, automatable occupations involving more physical contact were hit harder by the pandemic initially, although the at-risk and low-risk gap shrank over time during the recovery. As of August, the at-risk and low-risk gap was 7.3 percentage points for occupations with a high transmission risk, slightly higher than the 4.3 percentage points for low transmission risk occupations. The larger at-risk and low-risk gap between occupations that are less teleworkable and have a higher risk of virus transmission is consistent with the contention that the pandemic accelerated automation in occupations vulnerable to the pandemic.

[16] An occupation is considered as "teleworkable" if its teleworkable score is 0.5 or above; individual occupations' teleworkability data were obtained from github.com/jdingel/DingelNeiman-workathome.

[17] The hard-hit service sectors are industries with the largest decline in employment from January to April 2020, including rental and leasing services; arts, entertainment, and recreation; accommodation; food services and drinking places; and personal and laundry services, as well as sectors that with significant declines in their services, including retail trade and transportation and warehousing (Ding and Sanchez, 2020). See Table A3 in appendix for the share of automatable jobs, as well as the change in total employment, for major industries.

Figure 3: Share of Jobs with High Virus Transmission Risk, Low Teleworkability, or in Hard-Hit Sectors, January 2020

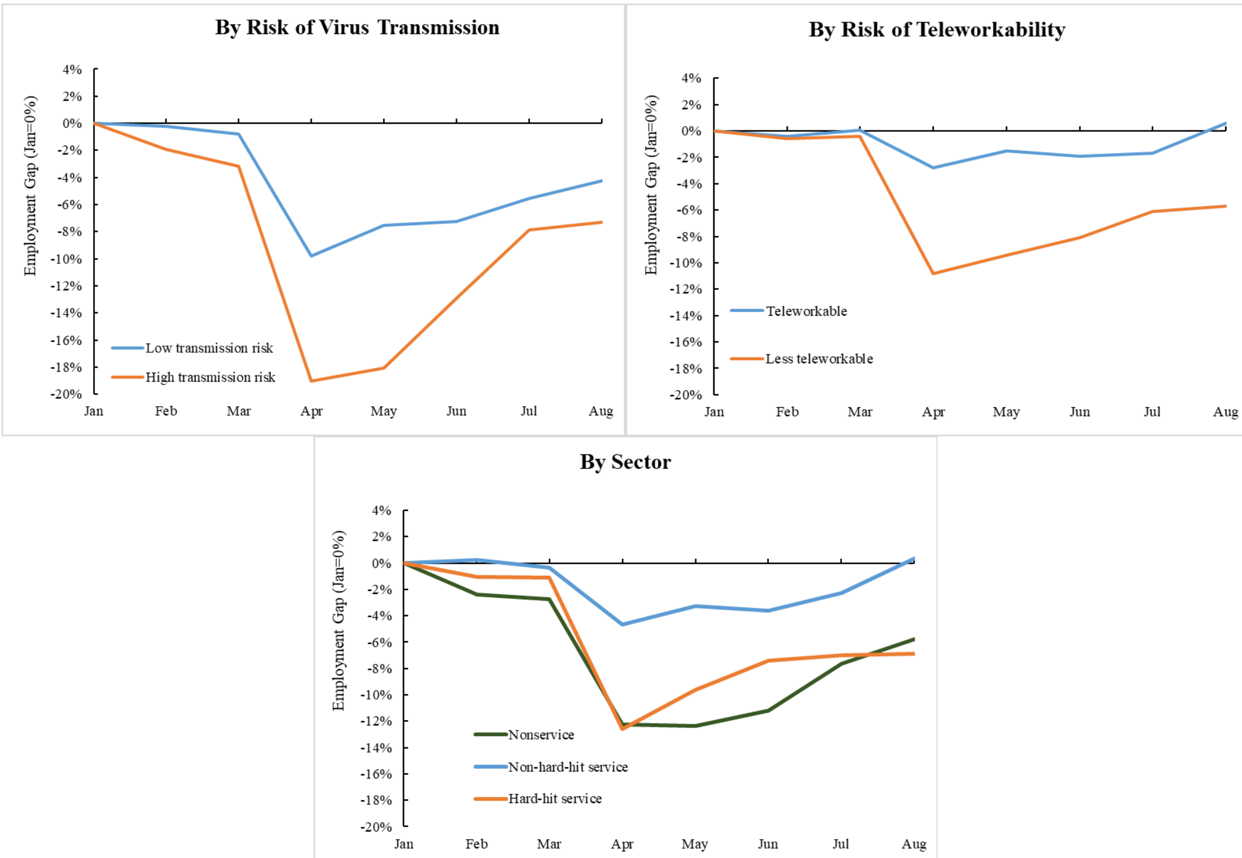


Note: Risk of virus transmission is based on O*NET's measure of physical proximity. Occupations with a score greater than 74.9 are considered high risk. Teleworkable occupations are those with a score greater than 0.5 in the Dingel and Neiman (2020) measure.
Sources: Authors' calculations based on data from the Census Bureau's (2020) Current Population Survey, O*NET, Dingel and Neiman (2020), and Leibovici et al. (2020)

Among different sectors, automatable occupations in the hard-hit service sectors experienced the largest job loss, as expected, with a loss 12.6 percentage points larger than the control group in April 2020 and 6.9 percentage points by August. While it is unsurprising to observe signs of accelerated automation in the hard-hit service sectors, the finding of larger job losses in automatable occupations in nonservice sectors is of greater concern. As Figure 4 shows, for every 100 precrisis jobs, at-risk occupations lost 12.3 more jobs by April than low-risk occupations in nonservice sectors, and as of August 2020, the gap was still 5.8 percentage points. One possible explanation for the large job losses in the nonservice sectors, which were not hit the hardest by the pandemic, is likely increased automation in these sectors since technologies to automate nonservice jobs, such as manufacturing jobs, are more mature and readily available than those for service jobs. The large and persistent gap between at-risk and low-risk occupations in nonservice sectors, as well as that for hard-hit service sectors, also could be considered a sign of forced automation during the pandemic.

Overall, the results suggest the COVID-19 crisis hit automatable jobs, especially those that do not allow remote work or those that have a higher risk of virus transmission. Obviously, not all displaced workers in automatable occupations were fully automated, as evidenced by the shrinking employment gap between at-risk and low-risk occupations during the recovery. Most of the job losses in these occupations are expected to recover quickly; however, the relatively large and persistent gap five months into the recovery between automatable and less automatable jobs in occupations with similar levels of vulnerability to the pandemic is worrisome. The results are consistent with the contention that the pace of automation has been accelerated during the pandemic, with the effect being larger in occupations that are more vulnerable to social distancing measures adopted in response to COVID-19.

Figure 4: Employment Gap Between At-Risk and Low-Risk Occupations by Occupation Virus Transmission, Teleworkability, and Sector



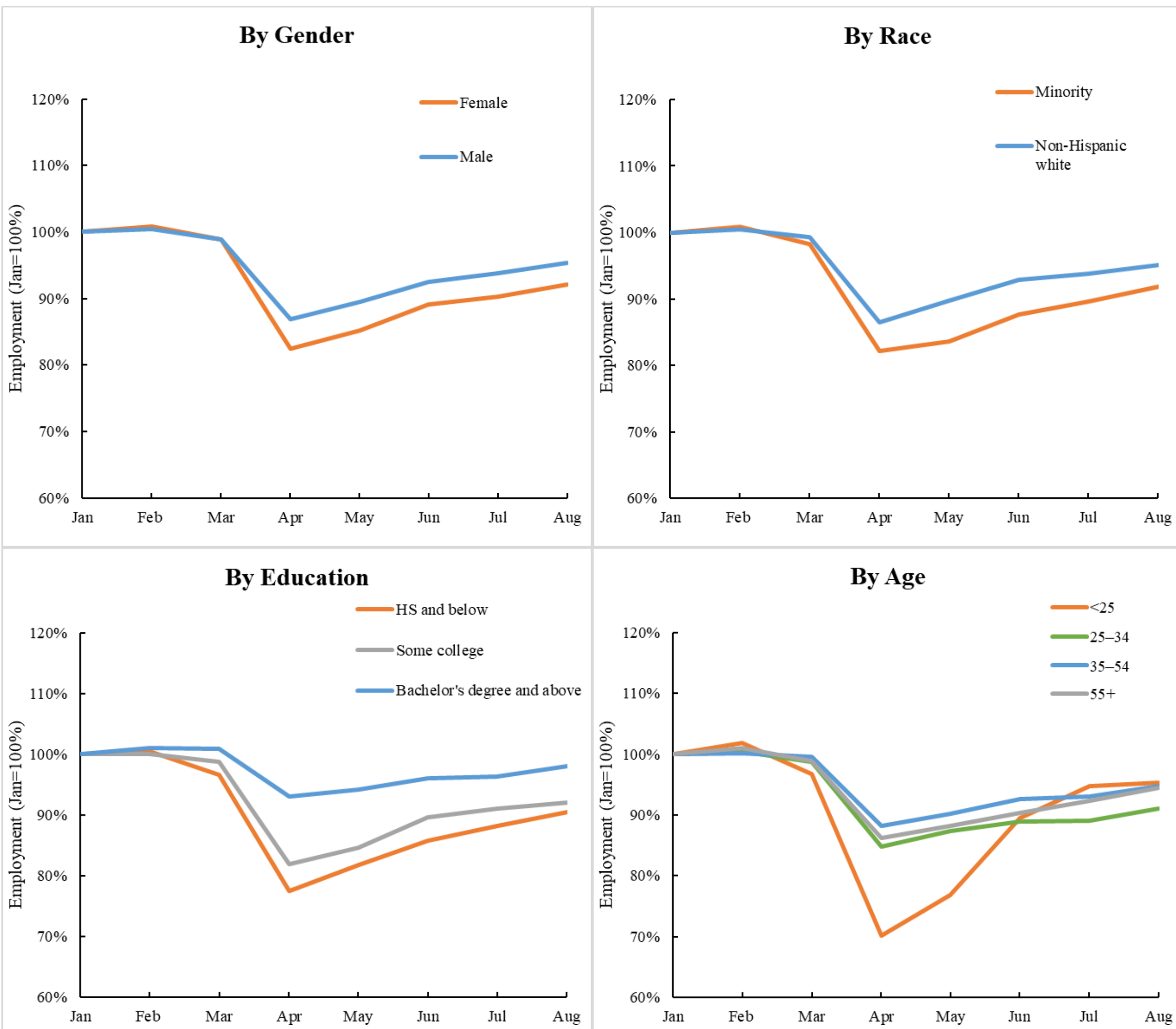
Note: Risk of virus transmission is based on O*NET's measure of physical proximity. Occupations with a score greater than 74.9 are considered high risk. Teleworkable occupations are those with a score greater than 0.5 in the Dingel and Neiman (2020) measure.
Sources: Authors' calculations based on data from the Census Bureau's (2020) Current Population Survey, O*NET, Dingel and Neiman (2020), and Leibovici et al. (2020)

4. Does the Likely "Forced Automation" Vary by Sociodemographic Groups?

The analysis below evaluates whether jobs held by disadvantaged workers are exposed to greater risk of automation during the pandemic. The CPS data provide detailed information on individual's age, gender, race and ethnicity, and educational attainment. The results generally suggest automatable jobs held by minority workers (nonwhite) were hit harder during the initial stage of the pandemic. Workers who are already vulnerable in the job market, such as younger (under 25), female, and less educated workers (without a bachelor's degree), experienced larger job losses in general, but the loss of automatable jobs held by these workers was not necessarily higher than that of their counterparts.

Figure 5 displays the number of jobs by workers' sociodemographic characteristics, as a share of their precrisis level, during the first seven months in 2020. The pattern is quite obvious: Female, younger (under 25 or 25–34), less educated, and minority workers experienced larger job losses than their counterparts. And as of August 2020, job losses for these more vulnerable groups were still much larger. The only exception was very young workers (under 25), which were hit extremely hard by COVID-19 in April, experienced a faster recovery than other age groups. By August, the youngest group had the lowest job loss rate among all age groups, possibly because of increased hiring of young workers in the summer; however, this could be temporary and seasonal.

Figure 5: Monthly U.S. Employment by Sociodemographic Groups in 2020



Note: Minorities are all Hispanic and/or nonwhite workers.
Sources: Authors' calculations based on Census Bureau's (2020) Current Population Survey

When we compare job losses between at-risk and low-risk occupations across different sociodemographic groups, we find that automatable jobs held by people of color experienced larger losses than others (Figure 6). The number of automatable jobs held by minority workers declined by 24.9 percent from January to April 2020, a loss 13.3 percentage points larger than the 11.6 percent decline for low-risk jobs held by minority workers. As of August 2020, at-risk jobs held by minority workers still had 7.0 more job losses per 100 than the control group. In contrast, at-risk jobs held by non-Hispanic white workers experienced a decline 9.5 percentage points larger than their corresponding control group by April and only 1.9 percentage points larger by August 2020. Obviously, there were much larger losses of automatable jobs held by minority workers than that for non-Hispanic whites by August 2020 (7.0 percentage points versus 1.9 percentage points). The finding of a larger loss of automatable jobs held by minority workers could be explained by the different occupation mix for Black and Latino Americans, such as their concentration in automatable occupations that are less likely to telework and bear a higher risk of virus transmission (e.g., cashiers, food service employees, and customer service representatives). In short, while far from conclusive, minority workers workers have been exposed to a greater risk of automation because the more automatable jobs they initially held were lost during the pandemic.

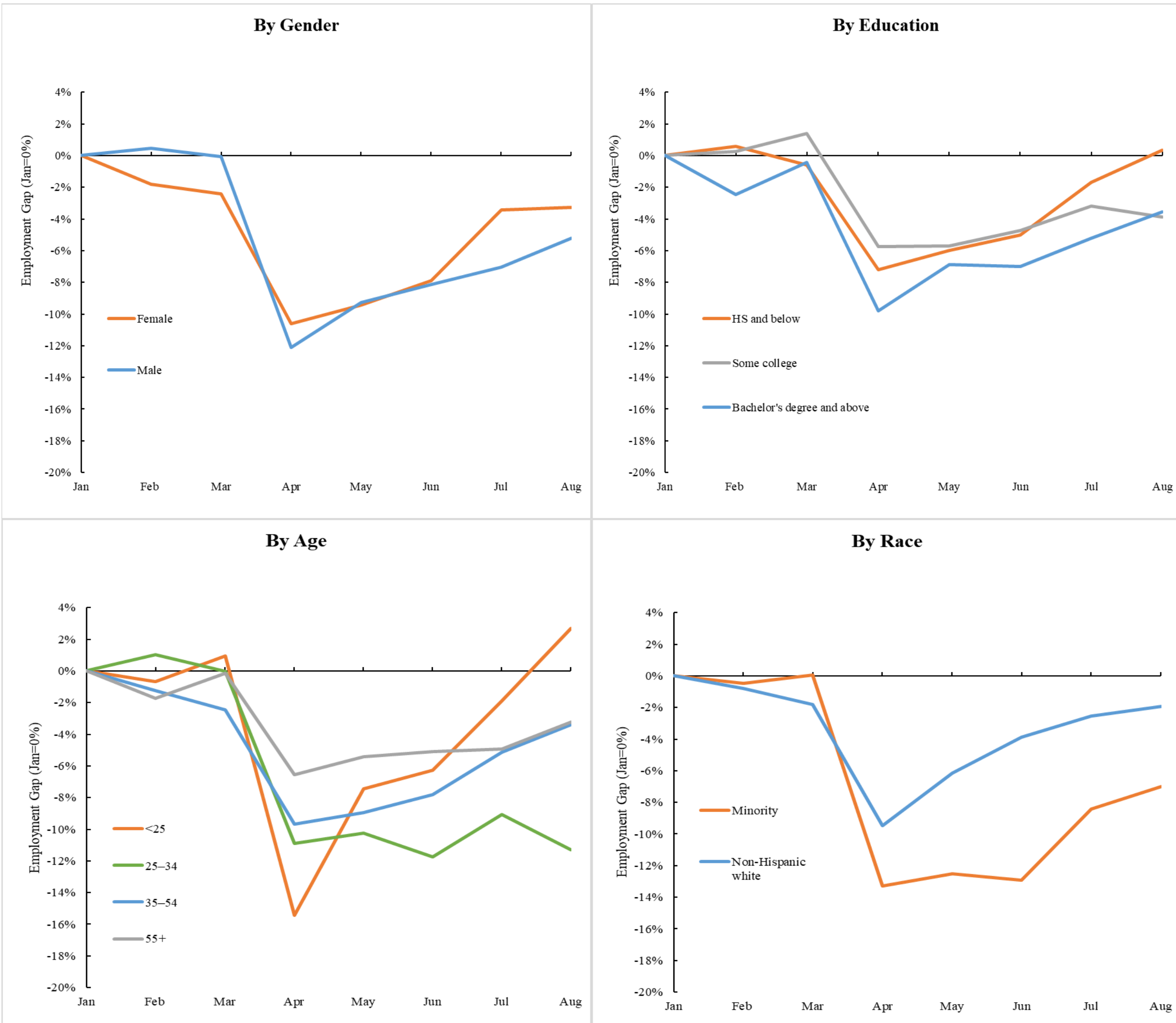
Turning to the patterns of job losses by workers of different gender, age, and educational attainment, the findings are quite consistent: Losses of automatable jobs held by more vulnerable workers were not necessarily higher than their counterparts by the end of our study period. For example, while female workers were more likely to lose their jobs during the pandemic in general, for every 100 precrisis jobs held by female workers, 3.3 more jobs were lost in at-risk occupations than that in low-risk ones by August, smaller than the at-risk and low-risk gap of 5.2 jobs for men. This may be explained by the greater concentration of manufacturing/construction automatable jobs by men, which are often more automatable than at-risk service jobs that are more likely to be held by women. Similar patterns can be found for jobs held by workers with or without a bachelor's degree and workers in different age groups. Actually, the gap between at-risk and low-risk occupations was slightly larger for jobs held by workers with a bachelor's degree or a higher degree than those without a bachelor's degree. One possible explanation is that it might be easier for the displaced workers who initially worked in low-skill and lower-paid service jobs to find an equivalent job during the recovery than highly specialized workers who lost their jobs.

Overall, the results suggest that the number of jobs held by more vulnerable workers dropped more precipitously during the pandemic. Particularly, minority workers who held automatable jobs experienced larger losses than others in the early stage of the pandemic, although the pattern for automation-induced job losses for other vulnerable populations is still unclear. Of course, the trend of forced automation for jobs held by more vulnerable workers may change over time if the recovery is further prolonged.

5. What Can We Learn from the Recovery from the Great Recession?

The previous three sections have documented larger job losses for occupations with a higher risk of automation in the initial stage of the COVID-19 crisis. Actually, the pattern is nothing new and just echoes similar concerns about automation in recent recessions. Although the timeline and circumstances of the COVID-19 crisis are different from those of the Great Recession, we show in this section that what happened during the last recession can still shed light on the potential impact of automation during the recovery from the current crisis.

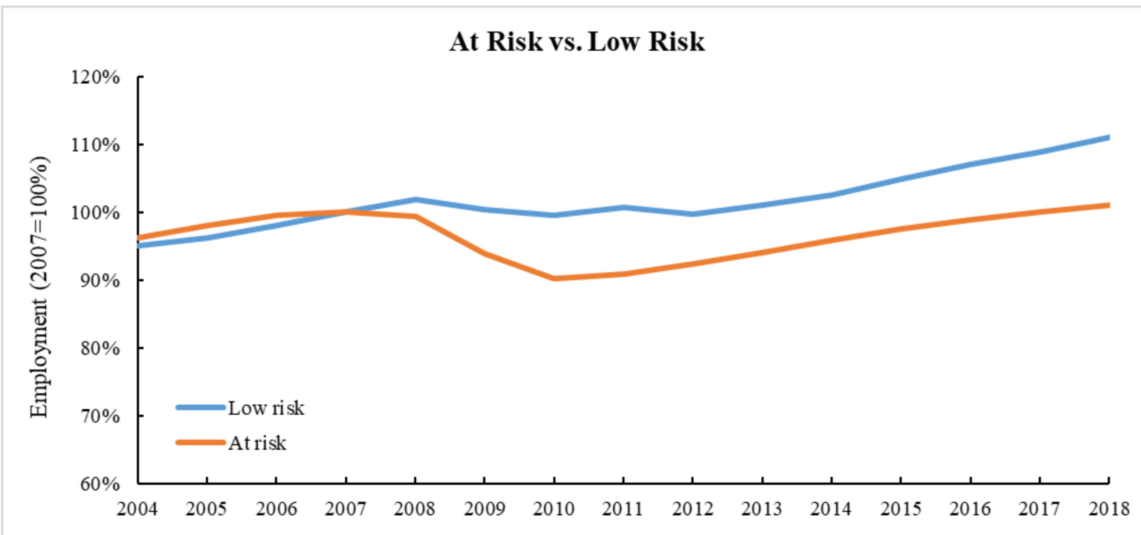
Figure 6: Employment Gap Between At-Risk and Low-Risk Occupations by Demographics



Note: Minorities are all Hispanic and/or nonwhite workers.
Sources: Authors' calculations based on data from Frey and Osborne (2017) and Census Bureau's (2020) Current Population Survey

We replicated the analysis in Section 2 based on the yearly employment data from the yearly Occupational Employment Statistics (OES) during the 2004–2018 period. At-risk occupations experienced a larger decline during the Great Recession than those with a low risk: At-risk occupations suffered a 9.7 percent decline in total employment from 2007 to 2010, larger than the decline of 0.4 percent for low-risk ones (Figure 7). Putting this in context, the at-risk and low-risk gap of 9.3 percentage points during the Great Recession was slightly smaller than the difference of 11.3 percentage points in April 2020 but larger than the gap of 4.2 percentage points as of August 2020. The increase in total employment of at-risk occupations was also no larger than that for low-risk occupations during the recovery from 2010 to 2018. Consequently, the job losses in automatable occupations became largely permanent: The total employment in at-risk occupations remained largely unchanged (a slight increase of 1.0 percent) from 2007 to 2018, compared with a much larger increase of 11.0 percent for low-risk occupations.[18] Analysis using alternative automation risk measures provides quite consistent results (Jaimovich and Siu, 2018).[19] These results clearly suggest occupations at risk of automation experienced a larger decline in their total employment during the Great Recession, and the losses became largely permanent during the recovery.

Figure 7: U.S. Employment by Automation Risk Level, 2004–2018



Sources: Authors' calculations based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2018)

Of course, the COVID-19 crisis differs from the Great Recession in important ways. First, the COVID-19 crisis was caused by a health crisis, while the Great Recession was initially caused by a financial crisis. Consequently, job losses induced by the pandemic have quite different sectoral composition than those from the Great Recession (Bartik, et al. 2020). The low-skill services and retail sectors of the economy that bear a higher risk of virus transmission were hit harder by the pandemic than other sectors, different from the high-paid construction and manufacturing sectors that initially suffered the most from the Great Recession. But many of the automatable jobs that experienced the largest decline after the Great Recession were still low-skill service jobs like

[18] The regression of individual occupations also confirms that occupations at risk of automation on average experienced a greater decline in total employment from 2007 to 2010 than low-risk occupations (14.6 percent), and the difference increased to 20.2 percent by 2018. Results are not included in the report but are available upon request.
[19] Our own analysis using occupations' routineness or exposure to robots measures yields generally consistent results (see Figure A3).

legal secretaries, administrative assistants, telemarketers, and payroll clerks.[20] Second, different from the Great Recession, many of the job losses during the COVID-19 crisis were expected to be temporary, and as our data showed early, almost 60 percent of job losses in April had recovered by August 2020; this is different from the Great Recession, which took about two years for the crisis to reach the bottom and took even longer for the recovery. So, on the one hand, it is reasonable to expect less automation during the pandemic than the Great Recession because of the unique nature and the likely shorter duration of the COVID-19 crisis. On the other hand, recent technological developments have made more previously safe jobs automatable. The pandemic also forced an experiment of various technologies and innovations that was unprecedented in its scale and scope. A prolonged recovery, seemingly under way now, would also lead to more permanent job losses in automatable occupations not directly impacted by the pandemic. The actual impact of automation thus could be either relatively modest or quite serious, ultimately depending on when the coronavirus can be contained and how firms and the government respond to automation technologies.

6. Summary and Implications

This empirical analysis on the relationship of automation and jobs during the first few months of the pandemic suggest COVID-19 has led to significantly larger job losses in more technically automatable occupations. It is still too early to conclude whether the larger job losses in automatable occupations we observed will become permanent. However, the massive job losses in these occupations exacerbated the job-replacing concerns about automation, as it is much easier for firms to replace displaced workers, instead of existing ones, with technology, not to mention the pandemic-induced long-term shifts in the labor market. Even if only a small share of automatable jobs lost during the pandemic are permanently replaced by technology, it would likely lead to inevitable adjustment pains for impacted workers.

Pandemic-induced automation is also likely to exacerbate many preexisting racial and economic disparities. The jobs threatened by automation are not evenly distributed across society. Jobs held by minority workers, for example, experienced larger losses during the pandemic, exposing these workers, who are already more disadvantaged in the labor market, to a greater risk of permanent job losses. Results also suggest jobs in hard-hit service sectors, in more automatable nonservice sectors, or in more automatable occupations that do not allow them to work from home already experienced larger losses during the pandemic, thus putting these jobs at a higher risk of being permanently replaced by technology. When trying to promote an equitable recovery from the pandemic, the groups that are threatened by both the health crisis and automation technology deserve more attention.

While we are still in the early stage of the recovery from the COVID-19 crisis, data accumulated in the first few months since the recovery began already illustrate some important trends and point out directions for future research and policy responses. The threat of automation-induced job losses needs to be monitored carefully. Case studies of specific automation technologies are also needed to help people understand the heterogeneity in the actual adoption of technologies,

[20] See Table A4 in the Appendix for a list of automatable occupations with the largest decline in employment from 2007 to 2018.

as well as the impact of individual technological innovations on jobs. As the pace of automation is likely being expedited by the pandemic, policymakers need to rethink how to improve the safety net for workers abruptly displaced by the pandemic, who also face an imminent risk of being replaced by technology, as well as how to prepare for the complex workforce transitions ahead induced by the potentially accelerated automation. The uncertain nature of the pandemic may cause a prolonged spell of joblessness for many displaced workers. For workers whose jobs were eventually replaced by technology, it may take years for them to settle down in more sustainable occupational opportunities. This could lead to unprecedented need for government interventions to support the jobless.

References

Angelucci, Manuela, Marco Angrisani, Daniel M. Bennett, Arie Kapteyn, and Simone G. Schaner. 2020. "Remote Work and the Heterogeneous Impact of COVID-19 on Employment and Health." NBER Working Paper No. 27749. Available at www.nber.org/papers/w27749.pdf.

Autor, David H. 2010. *The Polarization of Job Opportunities in the U.S. Labor Market: Implications for Employment and Earnings*. Washington, D.C.: Brookings Institution. Available at www.brookings.edu/research/the-polarization-of-job-opportunities-in-the-u-s-labor-market-implications-for-employment-and-earnings/.

Autor, David H. and Elisabeth B. Reynolds. 2020. *The Nature of Work After the COVID Crisis: Too Few Low-Wage Jobs*. Washington, D.C.: Brookings Institution. Available at www.brookings.edu/research/the-nature-of-work-after-the-covid-crisis-too-few-low-wage-jobs/.

Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matt Unrath, 2020. "Measuring the Labor Market at the Onset of the COVID-19 Crisis." NBER Working Paper No. 27613, available at www.nber.org/papers/w27613.

Barrero, Jose Maria, Nick Bloom and Steven J. Davis. 2020. "COVID-19 Is Also a Reallocation Shock." NBER Working Paper No. 27137, available at www.nber.org/papers/w27137.

Bureau of Labor Statistics. 2018. "Occupational Employment Statistics" (national), available at www.bls.gov/oes/tables.htm.

Census Bureau. 2020. "Basic Monthly Current Population Survey," available at www.census.gov/data/datasets/time-series/demo/cps/cps-basic.html.

Ding, Lei and Alvaro Sanchez. 2020. *What Small Businesses Will Be Impacted by COVID-19?* Federal Reserve Bank of Philadelphia Research Brief. Available at philadelphiafed.org/covid-19/covid-19-equity-in-recovery/what-small-businesses-will-be-impacted.

Ding, Lei, Elaine W. Leigh, and Patrick Harker, P. 2018. *Automation and Regional Employment in the Third Federal Reserve District*. Federal Reserve Bank of Philadelphia Special Report. Available at www.philadelphiafed.org/-/media/community-development/publications/special-reports/automation-and-regional-employment.pdf?la=en.

Dingel, Jonathan I and Brent Neiman. 2020. "How Many Jobs Can Be Done at Home?" NBER Working Paper No. 26948, available at www.nber.org/papers/w26948.

Foote, Christopher L. and Richard W. Ryan. 2015. "Labor Market Polarization over the Business Cycle." *NBER Macroeconomics Annual*, University of Chicago Press, 29(1): pp. 371–413.

Frey, Carl Benedikt and Michael A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change*, 114: pp. 254–80.

Hershbein, Brad and Lisa B. Kahn. 2018. “Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings.” *American Economic Review*, 108(7): pp. 1737–72.

Jaimovich, Nir and Henry E. Siu. 2020. “Job Polarization and Jobless Recoveries.” *Review of Economics and Statistics*, 102(1): pp. 129–47.

Leduc, Sylvain and Zheng Liu. 2020. “Can Pandemic-Induced Job Uncertainty Stimulate Automation?” Federal Reserve Bank of San Francisco Working Paper 2020-19. Available at doi.org/10.24148/wp2020-19.

Leibovici, Fernando, Ana Maria Santacreu, and Matthew Famiglietti. 2020. Social Distancing and Contact-Intensive Occupations. Federal Reserve Bank of St Louis, *On the Economy* blog. Available at www.stlouisfed.org/on-the-economy/2020/march/social-distancing-contact-intensive-occupations.

Montenovo, Laura, Xuan Jiang, Felipe Lozano Rojas, Ian M. Schmutte, Kosali I. Simon, Bruce A. Weinberg, and Coady Wing. 2020. “Determinants of Disparities in Covid-19 Job Losses.” NBER Working Paper No. 27132, available at www.nber.org/papers/w27132.

Mongey, Simon, Laura Pilossoph, and Alex Weinberg. 2020. “Which Workers Bear the Burden of Social Distancing Policies?” NBER Working Paper No. 27085, available at www.nber.org/papers/w27085.

Webb, Michael. 2019. “The Impact of Artificial Intelligence on the Labor Market.” Working paper, available at ssrn.com/abstract=3482150.

Appendix

Appendix A: Data and Methodology

2020 Employment Analysis

The 2020 employment analysis primarily uses data from the Census Bureau's Current Population Survey, which is a monthly survey of about 60,000 occupied households. The survey asks respondents about their activities during the week containing the 12th of the month. We also use the automation risk probability from Frey and Osborne (2017) to classify each occupation into two risk categories: Jobs in occupations with 70 percent risk or greater of being automated are defined as at risk, and those with less than a 70 percent risk are designated as low risk.

Since the Frey and Osborne data give a probability measure to each occupation specified in 2010 Standard Occupation Code (SOC) structure, each worker's primary job reported in the CPS data was linked to its corresponding 2010 SOC. First, using the crosswalk provided by the Census Bureau, we matched the Census occupational codes with their corresponding 2018 SOCs. Next, using the crosswalk between the 2018 and 2010 SOCs provided by the BLS, each occupation is linked to its corresponding six-digit 2010 SOC. While 389 occupational codes had a direct match between the Census, the SOC, and the Frey and Osborne measure, some structural differences between the 2010 and 2018 codes created three types of relationships: one-to-many, many-to-one, or many-to-many. We calculated the weighted average or manually assigned the probability of automation for the occupations that were not uniquely matched. For example, if the 2018 code was part of a 2010 occupation, then we assigned the probability value of the 2010 code to all the 2018 codes that constitute it. Furthermore, 135 census occupations are linked to a five-digit or higher SOC. For such cases, the assigned risk probability value is the weighted average[21] of the 2010 SOCs that compose the higher-level code.

After classifying each job with an automation probability value, we identified all survey respondents that were classified as employed-at work or employed-absent (i.e., PEMLR=1 or 2). We then estimated total employment by aggregating the composite final weight (PWCMPWGT) of respondents with a primary job in each risk category.

Alternative Measures of Automation Risk

As a robustness check, we used two alternative measures of risk. One of them is the widely used classification of routine versus nonroutine and cognitive versus manual. Following Foote and Ryan (2015), we grouped each occupation into two groups using the first two digits of the SOC: Codes starting with 11 to 39 are classified as nonroutine (occupations starting with 11 to 29 are cognitive nonroutine and those starting with 31 to 39 are manual nonroutine); those starting in 41 to 53 are defined as routine occupations.

Additionally, we matched each occupation with another measurements of automation risk, an occupation's robot exposure score defined in Webb's (2019).[22] The exposure to robots measure uses the overlap between the text of job task descriptions and the text of patents to measure the exposure of an occupation's tasks to robots (Webb, 2019). We consider an occupation with a high risk of being automated by robots if its exposure to robots score is 0.5 or above.

2004-2018 Employment Analysis

We primarily use data from the BLS's Occupational Employment Statistics (OES) for the 2004–2018 period at the national level. Each occupation is then matched with a probability for automation based on data from Frey and Osborne (2017). One limitation of this data set, however, is that it only provides automation probabilities for

[21] Weighted by the 2018 employment level obtained from OES data.
[22] Webb (2019) introduced three automation measures, including exposure to software, robots, and AI. This study focuses on exposure to robots measure only, which is more relevant since the pandemic hit occupations requiring physical contact harder than others. The other two measures focusing on technologies that are either too outdated (software) or too new and immature (AI) in the current recession are not considered.

occupations specified in the 2010 OES data set, the same year a structural change occurred in the SOC. Therefore, 40 of the 821 occupations in the 2004–2009 period, which uses the 2000 SOC, were not directly matched with a probability. Using a methodology similar to the match of CPS occupation code to SOC code, we calculated or manually assigned the probability of automation for the matched occupations.

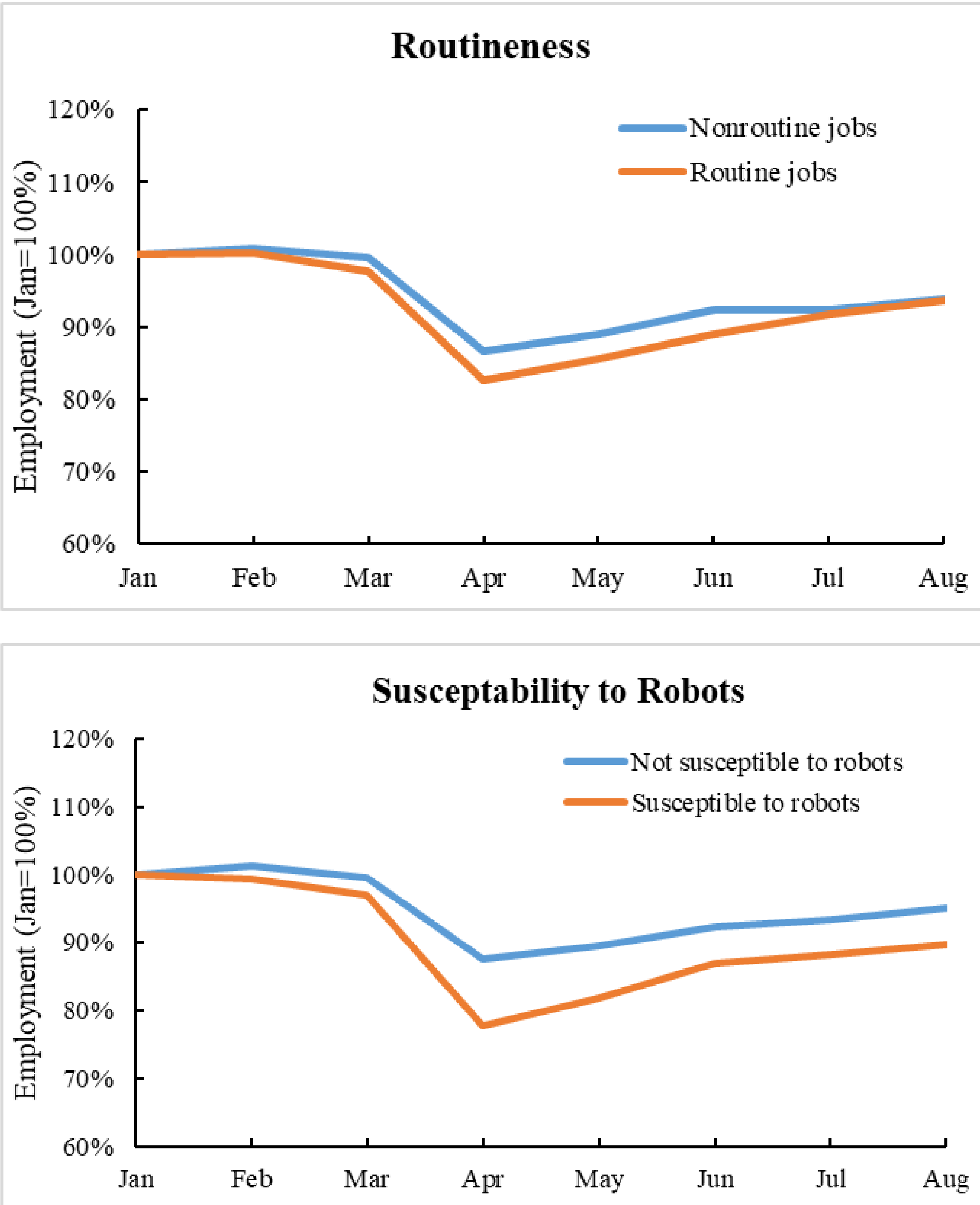
Regression Analysis

We used a simple difference-in-differences (DID) model to compare changes in total employment in occupations with a higher automation risk with those changes for lower-risk occupations before and during the pandemic. The difference-in-differences, thus, measures how COVID-19 impacts occupations with different automation risk differently. Empirically, the two-way, occupation-level DID model can be specified as:

$$Y_{it} = \beta_0 + \beta_1 AUTO_i + \beta_2(AUTO_i \times MONTH_t) + OCC_i + MONTH_t + \varepsilon_{it}$$

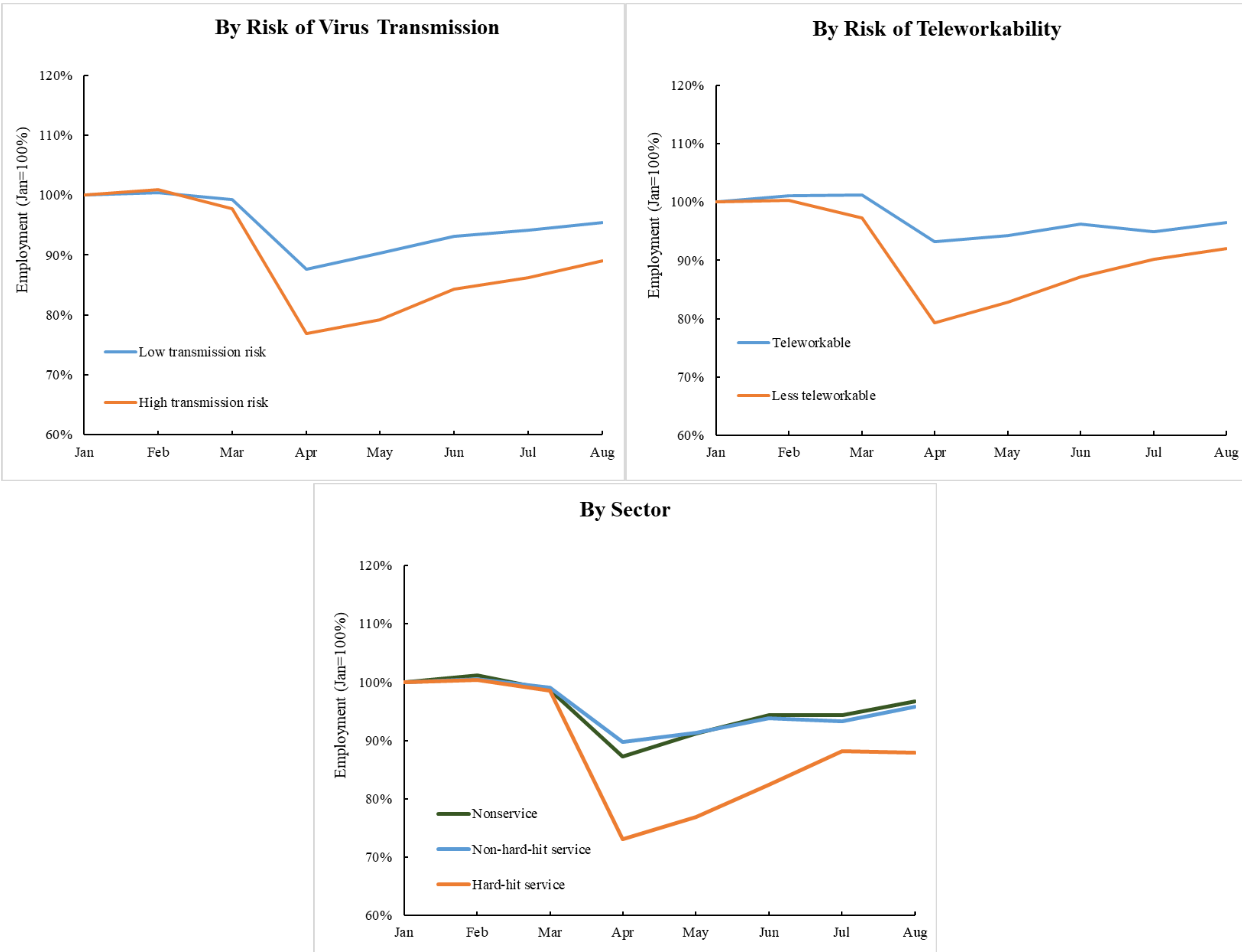
where Y_{it} represents a measure of total employment (in log) for occupation *i* in month *t* in 2020. $AUTO_i$ represents whether occupation *i* is more likely to be automated or not (either binary or categorical); this variable is ultimately omitted in the estimation because we include occupational fixed effects. $MONTH_t$ is monthly dummy and OCC_t is occupational dummy. $AUTO_i \times MONTH_t$ is the two-way interaction of the monthly and treatment dummies. The coefficient of the two-way interaction term β_2 is expected to capture the effects of automation on jobs for months during the pandemic. The model for the OES regression is similar, expect that we use yearly employment data based on SOC codes instead of monthly data based on the census occupational definitions in the regression. The CPS regression uses a panel data set of 4,151 occupation months. The CPS regression is based on the Census occupation definitions. All standard errors are clustered at the occupation level.

Figure A1: Monthly U.S. Employment by Alternative Automation Measures in 2020



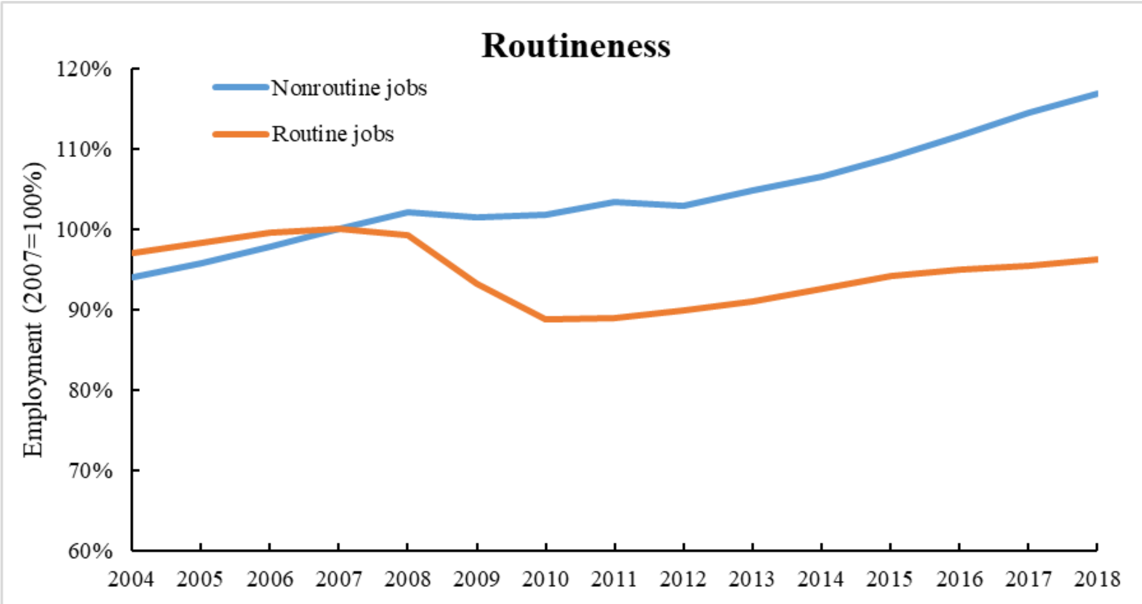
Sources: Authors' calculations based on data from Bureau of Labor Statistics (2020), Foote and Ryan (2015), and Webb (2019)

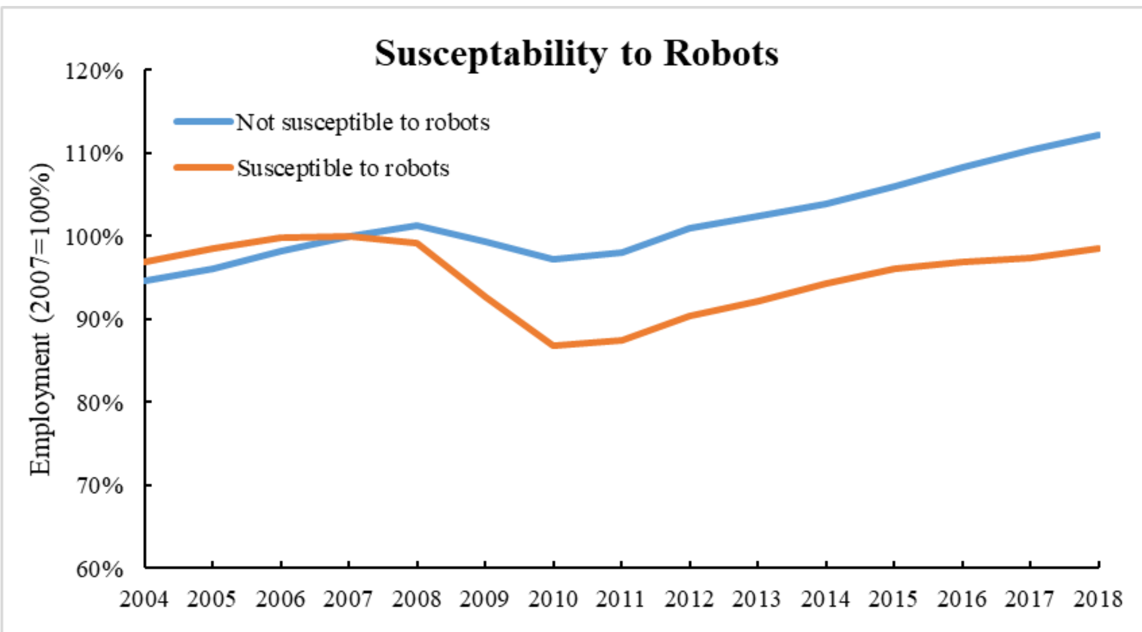
Figure A2: Monthly U.S. Employment by Occupation Virus Transmission, Teleworkability, and Sector



Note: Risk of virus transmission is based on O*NET's measure of physical proximity. Occupations with a score greater than 74.9 are considered high risk. Teleworkable occupations are those with a score greater than 0.5 in the Dingel and Neiman (2020) measure.
Sources: Authors' calculations based on data from the Census Bureau's (2020) Current Population Survey, O*NET, Dingel and Neiman (2020), and Leibovici et al. (2020)

Figure A3: U.S. Employment by Alternative Automation Measures, 2004–2018





Sources: Authors' calculations based on data from Foote and Ryan (2015), Webb (2019), and Bureau of Labor Statistics (2018)

Table A1: Total U.S. Employment by Automation Risk and Demographic Groups, 2020

Group	January 2020 Employment	April 2020 Employment	August 2020 Employment	% Change January to April	% Change January to August
By Risk					
Low risk	91,131,490	81,447,995	87,101,721	-10.6%	-4.4%
At risk	61,321,367	47,880,997	56,014,166	-21.9%	-8.7%
By gender					
Female	71,051,140	58,592,157	65,484,124	-17.5%	-7.8%
Male	81,401,717	70,736,835	77,631,762	-13.1%	-4.6%
By race					
Minority	58,036,224	47,700,449	53,330,108	-17.8%	-8.1%
Non-Hispanic white	94,416,633	81,628,543	89,785,779	-13.5%	-4.9%
By education					
HS and below	50,766,287	39,353,007	45,907,397	-22.5%	-9.6%
Some college	41,749,112	34,191,272	38,412,302	-18.1%	-8.0%
Bachelor's degree and above	59,937,458	55,784,714	58,796,188	-6.9%	-1.9%
By age					
<25	18,056,863	12,676,024	17,199,985	-29.8%	-4.7%
25–34	34,743,971	29,456,976	31,619,797	-15.2%	-9.0%
35–54	63,316,253	55,873,688	59,995,538	-11.8%	-5.2%
55+	36,335,769	31,322,305	34,300,567	-13.8%	-5.6%

Sources: Authors' calculations based on data from Frey and Osborne (2017) and Census Bureau's (2020) Current Population Survey

Table A2: Top 20 Hardest-Hit At-Risk Occupations in the U.S.

2018 Census Occupation Definition	Automation Risk Probability	Employment Level January 2020	Employmen t Change (January to April)	Employment Change (January to August)
Shuttle drivers and chauffeurs	70–95%	246,524	-66.8%	-86.2%
Weighers, measurers, checkers, and samplers, recordkeeping	95.0%	108,873	-51.8%	-71.8%
Hotel, motel, and resort desk clerks	94.0%	144,422	-52.8%	-56.6%
Bus drivers, school	70–95%	317,087	-58.2%	-55.8%
Highway maintenance workers	87.0%	147,803	-28.5%	-55.6%
Taxi drivers	70–95%	523,738	-44.0%	-53.7%
Food servers, nonrestaurant	86.0%	225,437	-27.1%	-46.1%
Electrical, electronics, and electromechanical assemblers	73.0%	122,188	-36.8%	-39.9%
Waiters and waitresses	94.0%	2,015,728	-64.0%	-38.7%
Transportation service attendants	83.0%	143,053	-41.2%	-38.0%
Production, planning, and expediting clerks	88.0%	307,777	-12.1%	-37.5%
Parts salespersons	98.0%	157,742	-31.1%	-36.7%
Painting workers	83.2%	201,468	-37.7%	-32.5%
Dishwashers	77.0%	240,804	-81.4%	-32.1%
Gambling services workers	95.5%	112,118	-83.9%	-31.5%
Food preparation workers	87.0%	1,076,291	-49.8%	-28.6%
Bill and account collectors	95.0%	127,648	-25.9%	-27.9%
Hosts and hostesses, restaurant, lounge, and coffee shop	97.0%	313,666	-63.4%	-27.3%
Barbers	80.0%	120,613	-52.8%	-26.4%
File clerks	97.0%	183,019	6.4%	-25.6%

*Census occupations are defined differently than occupations in the SOC structure. Therefore, the occupations listed in these table are not directly comparable to those listed in Table A.4
Note: This list excludes occupations with fewer than 100,000 workers as of January 2020. Occupations missing a probability value were manually assigned a risk category based on their description and similar occupations.
Sources: Authors' calculations based on data from Frey and Osborne (2017) and the Census Bureau's (2020) Current Population Survey

Table A3: Employment Change in At-Risk Occupations by Industry, 2020

	Sector Total Employment (January 2020)	Share of Employment in At-Risk Occupations (January 2020)	Employment Change in At-Risk Occupations (January to April)	Employment Change in At-Risk Occupations (January to August)
Hard-hit services	40,552,223	56.94%	-32.38%	-15.1%
Nonservice	29,220,107	52.58%	-18.50%	-6.1%
Non-hard-hit services	82,680,527	27.66%	-13.65%	-3.9%
Agriculture	2,285,550	52.2%	-3.5%	-8.1%
Mining	836,637	38.8%	-7.8%	-42.9%
Construction	10,807,495	53.9%	-18.9%	0.1%
Manufacturing	15,290,426	52.5%	-20.9%	-8.8%
Wholesale and retail trade	19,821,541	52.7%	-21.1%	-8.2%
Transportation and utilities	8,872,510	60.4%	-12.8%	-10.1%
Information	2,753,667	16.6%	-28.7%	-20.5%
Financial activities	10,629,885	51.5%	-9.4%	-2.7%
Professional and business services	19,012,827	29.2%	-13.8%	-0.1%
Educational and health services	33,572,556	17.9%	-19.8%	-6.2%
Leisure and hospitality	13,976,546	61.5%	-49.7%	-25.3%
Other services	7,356,533	30.5%	-30.7%	-5.0%
Public administration	7,236,685	25.3%	-8.4%	-4.2%

Note: The hard-hit service sectors include rental and leasing services, arts, entertainment, and recreation, accommodation, food services and drinking places, personal and laundry services, retail trade, and transportation and warehousing. A small number of jobs with missing value on the automation probability were dropped from the total employment.
Source: Census Bureau's (2020) Current Population Survey

Table A4: Top 20 Hardest-Hit At-Risk Occupations in the U.S., 2007–2018

2018 SOC Occupation Title*	Automation Risk Probability	Employment Level 2007	Employment Change (2007 to 2018)
Computer Operators	78.0%	117,380	-70.4%
Executive Secretaries and Executive Administrative Assistants	86.0%	1,517,410	-62.4%
Word Processors and Typists	81.0%	139,420	-61.9%
Switchboard Operators, Including Answering Service	96.0%	160,200	-55.3%
Telemarketers	99.0%	354,000	-53.6%
Machine Feeders and Offbearers	93.0%	143,140	-53.6%
File Clerks	97.0%	214,590	-48.7%
Postal Service Mail Sorters, Processors, and Processing Machine Operators	79.0%	201,430	-48.5%
Brickmasons and Blockmasons	82.0%	116,290	-45.0%
Data Entry Keyers	99.0%	286,540	-39.0%
Bill and Account Collectors	99.0%	409,570	-38.6%
Mail Clerks and Mail Machine Operators, Except Postal Service	99.0%	138,990	-38.0%
Order Clerks	99.0%	255,670	-37.7%
Legal Secretaries	99.0%	266,180	-33.5%
Information and Record Clerks, All Other	99.0%	233,180	-33.4%
Sewing Machine Operators	99.0%	200,340	-31.9%
Helpers--Installation, Maintenance, and Repair Workers	99.0%	153,320	-31.5%
Payroll and Timekeeping Clerks	99.0%	201,940	-28.7%
Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	99.0%	254,160	-26.6%
Drywall and Ceiling Tile Installers	99.0%	137,570	-25.9%

*Census occupations are defined differently than occupations in the SOC structure. Therefore, the occupations listed in these table are not directly comparable with those listed in Table A.2
Note: This list excludes occupations with fewer than 100,000 workers as of 2007.
Sources: Authors' calculations based on data from Frey and Osborne (2017) and Bureau of Labor Statistics (2018)

Table A5: Data Sources

Data	**Source**	**Link**
Monthly Employment in 2020	Census Bureau's Current Population Survey	https://www.census.gov/data/datasets/time-series/demo/cps/cps-basic.html
2004–2018 employment by occupation	Bureau of Labor Statistics Occupational Employment Statistics	https://www.bls.gov/oes/tables.htm
Automation probability by 2010 SOC	Frey and Osborne (2017)	https://www.sciencedirect.com/science/article/abs/pii/S0040162516302244
Physical proximity score by 2010 SOC	O*NET and Leibovici et al. (2020)	https://www.onetonline.org/find/descriptor/result/4.C.2.a.3?a=1
Teleworkability score by 2010 SOC	Dingel and Neiman (2020)	https://github.com/jdingel/DingelNeiman-workathome
Routine Categories	Foote and Ryan (2015)	https://www.journals.uchicago.edu/doi/full/10.1086/680656
Exposure to robots score by 2010 SOC	Webb (2019)	https://www.michaelwebb.co/