Gunadi, Christian; Ryu, Hanbyul

Working Paper

Does the Rise of Robotic Technology Make People Healthier?

GLO Discussion Paper, No. 600

Provided in Cooperation with:
Global Labor Organization (GLO)

Does the Rise of Robotic Technology Make People Healthier?

Christian Gunadi* Hanbyul Ryu†

July 9, 2020

Abstract

Technological advancements bring changes to our life, altering our behaviors as well as our role in the economy. In this paper, we examine the potential effect of the rise of robotic technology on health. The results of the analysis suggest that higher penetration of industrial robots in the local labor market is positively related to the health of the low-skilled population. A ten percent increase in robots per 1,000 workers is associated with an approximately 10% reduction in the fraction of low-skilled individuals reporting poor health. Further analysis suggests that reallocation of tasks and reduction in unhealthy behavior partly explain this finding.

JEL Classification: I10, I13, J24, O33

Keywords: Automation, Robots, Health

*christian.gunadi@email.ucr.edu. Department of Economics, UC Riverside, CA 92521, USA

†hbryu@kiep.go.kr. Department of New Southern Policy, Korea Institute for International Economic Policy, Sejong-si 30147, South Korea

1 Introduction

The use of industrial robots has been rising rapidly in the United States. Between 2005 and 2017, the number of robots per 1,000 workers increased by about 70% (Figure 1). At the same time, there are questions about how the rapid implementation of robots affects society. Most of the recent studies have been focused on the labor market effects of robot adoption in the local economy (Acemoglu and Restrepo, 2020a; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020b; Giuntella and Wang, 2019). These studies generally found that the rise of robotic technology harms the labor market prospect of low-skilled workers. Relatively few studies, however, examine how exposure to robots affect the other aspects of society. An exception is a work by Anelli et al. (2019), which found that a more intense robot penetration in the local labor market led to a decline in new marriages and an increase in both divorce and cohabitation, partly by rising economic uncertainty and lowering the relative marriage-market value of men.

In this paper, we examine the potential effect of higher robot exposure on the health of the low-skilled population. We postulate that higher penetration of robots in a local labor market improves the health of low-skilled individuals in the locality through two channels. First, robots mainly replace the physically demanding tasks usually done by low-skilled workers, nudging these workers toward occupations with lower intensity of physical tasks, improving their health. Second, the worsening labor market conditions will lead to a reduction in unhealthy behaviors, such as smoking. Indeed, the literature has documented evidence that mortality rate is pro-cyclical (Ruhm, 2000; Neumayer, 2004; Gerdtham and Ruhm, 2006), partly because of reductions in job-related stress and individuals adopting healthier lifestyle during economic downturns (Ruhm and Black, 2002; Ruhm, 2005).

We begin our analysis by examining the relationship between the rise of robotic technology and health. We found evidence that higher exposure to robots is positively related to the health of the low-skilled population. A ten percent increase in robots per 1,000 workers is associated with 0.5, 1.3, and 0.6 percentage points decline in the fraction of low-skilled population reporting poor health, work disability, and ever quit a job because of health reasons. Evaluated at the mean, these estimates correspond to an approximately 10% decrease in each of the outcomes. Examining the mechanisms behind these findings, we found evidence of the reallocation of tasks. A ten percent increase in robots per 1,000 workers is associated with approximately 2% reduction in the fraction of low-skilled workers employed in occupations classified as physically demanding.[1] Similar findings are found for employment in risky jobs. The results of the analysis suggest that a ten percent increase in robots per 1,000 workers is associated with approximately 9% and 4% declines in the fraction of low-skilled workers employed in high fatality rate occupations and high injury rate industries, respectively. We fail to find evidence that the fraction of the low-skilled population identified as a current or everyday smoker is affected by robot exposure. However, there is evidence that an increase in robot exposure is associated with a lower number of cigarettes per day consumed by everyday smokers. This finding suggests that the effect of robot exposure on health that is coming through changing smoking behavior, if there is any, is likely to be the result of a reduction in smoking intensity.

[1]As described later, we use the Department of Labor O*NET data to classify occupations with high physical tasks requirement.

This paper is related to a growing literature examining the impacts of the industrial robot. Most of these studies have been focused on the labor market effects of robot exposure. Examining the impacts of robots across U.S. commuting zones, Acemoglu and Restrepo (2020a) found strong negative effects of robots on employment and wages, especially among low skilled workers. Graetz and Michaels (2018) found that increased robot use is associated with higher labor productivity. However, they also found evidence that low-skilled workers lose out from the adoption of industrial robots.[2] Analyzing the effect of robots across cities in China, Giuntella and Wang (2019) found a large negative impact of robot exposure on employment and wages of Chinese workers, especially those who are low-skilled. Relatively few studies, however, examine how robots affect the other socio-economic outcomes. An exception is the work by Anelli et al. (2019), which found that higher adoption of robots in the local labor market affects the family formation, decreasing new marriages and increasing both divorce and cohabitation. We contribute to this literature by examining the potential role of robotic technology in improving the health of the population, especially those who are low-skilled.

This paper is also related to studies that examine the relationship between economic conditions and health. The seminal work by Ruhm (2000) found that mortality rate in the United States is procyclical.[3] Subsequent studies have found that this relationship hold in other countries (Neumayer, 2004; Granados, 2005; Gerdtham and Ruhm, 2006; Lin, 2009). The reason why this is the case, however, is still inconclusive. Ruhm and Black (2002) and Ruhm (2005) argue that reduction in

[2]This is unlike the effect of Information and Communication Technology (ICT), which mainly adversely affecting workers in the middle of skill distribution (Autor et al., 2003; Goos et al., 2014; Michaels et al., 2014).

[3]It is worth noting that a follow-up study by Ruhm (2015) suggests that mortality has shifted from strongly procyclical to weakly related to economic conditions in recent years.

unhealthy behaviors, such as drinking and smoking, partly explain why mortality decrease during economic downturns. A more recent study by Stevens et al. (2015) argues that lower quality of health care during economic expansion may explain the observed negative relationship between improvement in economic conditions and health. We contribute to this literature by documenting that worsening economic conditions due to the rise of robotic technology is associated with an improvement in health status among the low-skilled population and by offering potential mechanisms driving this relationship.

The rest of the article is constructed as follows. The next section describes the data used in the main analysis. Section 3 describes the empirical methodology. Section 4 documents the main finding. Section 5 explores the potential mechanisms explaining the main finding. Section 6 concludes.

2 Data

2.1 IFR Robot Data

We obtain the statistics on the operational stock of robots from the International Federation of Robotics (IFR). The statistics come primarily from the information provided by nearly all industrial robot suppliers to the IFR Statistical Department. The IFR data has information on the operational stock of "industrial robots" in more than 50 countries from 1993 to 2017, defined as "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications."

There are a few limitations of using IFR data. First, the statistics on the operational stock of robots are only available at the national level across the years. To obtain a measure of robot exposure at the local level, similar to recent studies (Acemoglu and Restrepo, 2020a; Graetz and Michaels, 2018; Giuntella and Wang, 2019), we use the variation in the initial distribution of industrial employment in U.S. localities and the difference in robot use across industries over time. The intuition is that cities that are historically more dependent on robot-intensive industries will have a higher number of robots per worker compared to other areas. Second, the IFR industrial classification is coarse, and it is only available since 2004, limiting our analysis period to 2004 onwards.[4] Additionally, not all robots are classified into one of IFR industry classification. For those that are unclassified, we allocate it to each industry in the same proportion as the classified robot data.

Using the information available from the IFR data, we constructed the robot exposure measure at the local level as follows:

$$Robots_{mt} = \sum_{j=1}^{J} \pi_{mj,1960} \times \frac{R_{jt}}{L_{j,1960}} \tag{1}$$

where $\pi_{mj,1960}$ is the share of industry j employment in MSA m in 1960. We use the share of industry in 1960 to focus on the city's specialization in industries that predates the rise of robots in the early 1990s. R_{jt} is the total stock of robot employed in industry j at time t. $L_{j,1960}$ is the number of workers employed in industry j in 1960. It follows that the robot exposure measure, $Robots_{mt}$, predicts that cities

[4]We use the broad IFR industry classification in creating the robot exposure measure: food/beverages and tobacco products, textiles, wood products, paper products, plastic and chemical products, glass/ceramics and other mineral products, metal, electronics, automotive, other transport equipment, other manufacturing branches, agriculture, mining, utilities, construction, education, and all other non-manufacturing branches.

that are more dependent on robot-intensive industries in 1960, partly because these cities have comparative advantages (i.e., resources, location) to specialize in those industries, will have a higher number of robots per worker today.

On average, there are 3.32 robots per 1,000 workers across the cities in our sample (Table 1). Many of the cities with the highest predicted robot exposure are located in the Midwest (Appendix Table 1). This is unsurprising since the automotive industry, which is the top robot-intensive industry (Appendix Table 2), is mainly concentrated in this region.

2.2 Health Status Data

The measures of health used in our analysis are obtained from the Current Population Survey (CPS) available on IPUMS (Flood et al., 2020). Administered monthly to over 65,000 households in the United States, CPS provides information on education, labor force status, and other aspects of the U.S. population. Over time, the CPS has added supplemental information on special topics such as health status and tobacco use in some months. The health status information, in particular, is available starting from 1996 in March CPS (CPS-ASEC). Throughout the analysis, we focus on the sample of individuals between the ages of 25 and 60 to avoid potential bias associated with changes in perceived/actual health after retirement (Coe and Zamarro, 2011; Mazzonna and Peracchi, 2012).

The health status in March CPS indicates an individual's health on a five-point scale (Excellent, Very Good, Good, Fair, or Poor). Specifically, the question is worded as follows: "Would you say your health in general is excellent, very good, good, fair, or poor?" We use this information to construct our main outcome: the share of the population in a city reporting poor health. In addition to health status, the March CPS also asks additional questions with regards to work disability and whether an individual ever quit a job because of health reasons. We use this information to construct additional health outcomes in the analysis. In an average city, the fraction of low-skilled population with no high school diploma reporting poor health is higher than their high-skilled counterparts: five percent of the low-skilled population reports that they are in poor health, while only 2 percent of the high-skilled population with at least a high school diploma reports that they are in poor health (Table 1).[5] Similar patterns between low- and high-skilled populations are observed for the fraction of population reporting work disability or ever quit a job because of health reasons.

3 Empirical Methodology

To examine the effect of robot exposure on health, we estimate the following empirical specifications:

$$y_{ct} = \delta_c + \delta_t + \beta_1 \ln(Robots_{c,t-2}) + X'_{ct}\beta_2 + \varepsilon_{ct} \tag{2}$$

where y_{ct} is the outcome for Metropolitan Statistical Area (MSA) c at time t. As mentioned in the previous section, we consider three health outcomes: the share of population reporting poor health, the share of population reporting work disability, and the share of population reporting ever quit a job because of health reasons. Our main coefficient of interest is β_1, which corresponds to unit increase in y following

[5]Throughout the paper, we define low-skilled as individuals with no high school diploma, while high-skilled is defined as those with at least a high school diploma.

an increase of one in the natural log of robots per 1,000 workers. We lagged the effects since it should take some time for individuals to adjust to an increase in robot exposure. X_{ct} is a vector of city-level control variables which include the population share of blacks, the population share of females, and the unemployment rate. δ_c and δ_t are MSA and year fixed effects, respectively. All regressions are weighted by the MSA population in 2000. Unless otherwise specified, our period of the analysis is 2006 to 2017. This is because the earliest robot by industry data is only available starting from 2004, and the latest IFR data that we can obtain is 2017. We include all MSA in IPUMS 5% 1960 Census that can be consistently identified in March CPS between 2004 and 2017 in our analysis.

Since we use predicted rather than actual robot exposure, there are fewer concerns that local unobserved factors will bias our estimates. However, to further address the endogeneity concerns, we use the variation in the robot use across industries in the European countries as an instrument, similar to Acemoglu and Restrepo (2020a) and Giuntella and Wang (2019). The main idea is that factors that contribute to the rise of robots in these other economies are unlikely to be correlated with unobserved factors affecting health in U.S. localities. Specifically, the instrument is constructed as follows:

$$Robots_{mt} = \sum_{j=1}^{J} \pi_{mj,1960} \times \frac{R_{jt}^{EU}}{L_{j,1960}} \tag{3}$$

where the definition of the variables is the same as before except for R_{jt}^{EU}, which is now defined as the total operational stock of industrial robots in European countries.[6]

[6]We use the sum of operational stock of robot in the United Kingdom, Finland, Denmark, France, Norway, Spain, and Sweden to construct the instrument.

To be valid, this instrument must fulfill two conditions. First, the instrument must be strongly correlated with the endogenous variable. The first-stage analysis results suggest that this is indeed the case (Appendix Table 3). The robust F-statistics are around 27, well above the Staiger and Stock (1994) rule of thumb of 10. The interpretation of the estimate is that a one percent increase in predicted robot exposure constructed using the variation in the robot use across industries in the European countries is associated with a roughly 0.5% rise in the predicted robot exposure in the U.S. cities. Second, the instrument must not be correlated with unobserved local factors affecting the health of individuals in U.S. localities. Although this condition is essentially untestable, we will provide supporting evidence that this condition is fulfilled in the next section.

4 Results

4.1 Main Findings

Before reporting the results from our main empirical specifications, we present the visual evidence on the relationship between robot exposure and health in Figures 2 and 3. We separate the analysis by two skill groups: low-skilled is defined as individuals with no high school diploma, while high-skilled is defined as those with at least a high school diploma. This is based on our hypothesis that the rise of robotic technology mainly substitutes for physically demanding tasks that were usually done by the low-skilled workers, nudging these workers towards occupations that are less physically demanding. Therefore, we should see that the effect of robots on health to be concentrated among the low-skilled population. Consistent with this hypothesis, we see that cities that had a high growth of robots per 1,000 workers between 2005 and 2017 experienced a decline in the share of low-skilled population reporting poor health (Figure 2a). The slope of the fitted line implies that a one percent increase in robot exposure is associated with a 1.13% decline in the fraction of low-skilled population reporting poor health. Although it is imprecisely estimated, we also see there is a negative relationship between the growth of robots per 1,000 workers with other measures of health outcome such as the share of low-skilled population reporting work disability or ever quit a job because of health reasons (Figures 2b and 2c).

On the other hand, there is not much evidence that the health outcomes for high-skilled individuals are affected by the rise of robotic technology (Figure 3). The slope of the fitted line suggests that there is a positive relationship between the growth of robot exposure and the fraction of the high-skilled population reporting poor health, but this estimate is small in magnitude and not statistically significant (Figure 2a). Qualitatively similar findings are found for the share of high-skilled population reporting work disability and ever quit a job because of health reasons (Figures 2b and 2c).

We report the results from our main empirical specifications in Table 2. Similar to visual evidence, the effects of robot exposure are mainly concentrated on the low-skilled population. A ten percent increase in robots per 1,000 workers is associated with about 0.3 percentage point decrease in the share of low-skilled population reporting poor health (Column 2 of Panel A). The results from the IV model suggest that this estimate is an overestimation of the true effect (~ 0.5p.p.). Evaluated at the sample mean, this estimate corresponds to about a 10% decline. Qualitatively similar findings are found for the other health outcomes: a one percent increase in robot exposure is associated with approximately 1.3 and 0.6 percentage points decline in the share of low-skilled population reporting work disability and ever quit a job for health reasons, respectively.

On the contrary, the estimates on the high-skilled population are smaller in magnitude and not statistically different from zero. At a 90% significance level, evaluated at the sample mean, for a 10% increase in robots per 1,000 workers, we can rule out an effect size larger than a 4% decline in the fraction of high-skilled population reporting poor health. The results from the IV model suggest a larger magnitude of the effect, but it is not statistically significant. Qualitatively similar results are obtained for the other health outcomes.

In sum, the results of the analysis in this section document evidence of a negative relationship between the rise of robotic technology and the fraction of low-skilled population reporting poor health. However, the mechanism driving this finding is still unclear. The next sections are devoted to checking the robustness of this finding as well as exploring the potential mechanisms explaining this result .

4.2 Robustness Checks

In the main empirical specifications, we choose to measure the two-year lagged effects of robot exposure, mainly because it should take some time for individuals to adjust in response to the rise of robotic technology in their locality. However, this choice may seem arbitrary. Therefore, we check the robustness of our findings when one- or three-year lagged robot exposures are used in the analysis (Appendix Table 4). Although some of the estimates become imprecisely estimated, the results of this exercise are largely in line with the findings from the main empirical specifications.

Another concern is that our findings may be driven by an outlier city with high growth of robot exposure experiencing a large decline in population reporting poor health. To check for this, we conducted a leave-one-city-out analysis, excluding one city in the sample one by one and re-estimating the effect. The results of this exercise are reported in Figure 4. For the fraction of the low-skilled population reporting poor health, the range of the estimates is quite narrow. Most of the estimates lie between -0.030 and -0.038 (Figure 4a). In Figure 4b, we also report the uncertainty around the estimates. There is no evidence that the main findings are driven by a specific city. Similar findings are also found for other health outcome measures.

Finally, Goldsmith-Pinkham et al. (2018) argues that the empirical specifications in which the variable of interest is constructed using a shift-share approach (equation 1) are similar to difference-in-differences methodology. In other words, the rise of robotic technology in the 1990s can be thought of as a 'policy' shock, and the industry shares serve as a proxy for the exposure to the shock. Cities that rely more on industries that are experiencing a higher rate of automation because of robotic technology will be more exposed to the shock. In this case, the assumption for the estimates to be valid is that cities that were experiencing high growth of robot per 1,000 workers in 2005-2017 period would have a similar change in the fraction of low-skilled population reporting poor health as cities with low growth of robot exposure in the absence of the rise of robotic technology in the 1990s. It is not possible to test for this assumption directly, but we can provide supporting evidence that this assumption is met by checking the pre-1990 trends. In Figure 5, we graph the relationship between the 2005-2017 growth of robots per 1,000 workers and the

1980-1990 growth of low-skilled population reporting work disability. The slope of the fitted lines suggests that the pre-1990 trend of work disability rate between cities that had a high growth of robot exposure in the 2005-2017 period and those with low growth is similar. Unfortunately, information on poor health status and on whether an individual ever quit a job for health reasons in 1980 and 1990 IPUMS 5% Census is not available, limiting the analysis only on the work disability rate. Nonetheless, the finding in Figure 4 further supports the validity of the estimates obtained in the main empirical analysis.

5 Potential Mechanisms

5.1 Reallocation of Tasks

The analysis in the previous section documents evidence of a negative relationship between robot exposure and the share of low-skilled population reporting poor health outcomes. However, it is unclear how the rise of robotic technology may affect health. We hypothesize that robots mainly substitutes for the physically demanding tasks usually done by low-skilled workers, nudging these workers towards occupation with less physical tasks. In this subsection, we examine whether there is evidence to support this hypothesis from the data.

To examine the potential reallocation of tasks in response to the growth in robots per 1,000 workers, we obtain information on the importance of physical abilities in a given occupation from the U.S. Department of Labor O*NET dataset. O*NET ratings reflect experts' evaluation of how important an ability is in the occupation. Within physical ability group, O*NET measures the importance of the following abilities in a standardized scale ranging from 0 (min) to 100 (max): dynamic flexibility, dynamic strength, explosive strength, extent flexibility, gross body coordination, gross body equilibrium, stamina, static strength, and trunk strength.[7] Unfortunately, not all occupations in O*NET occupation codes can be crosswalked to IPUMS consistent occupation codes (OCC1990). However, we manage to assign physical abilities score to 315 out of 341 occupations listed in IPUMS OCC1990. We then took an average of the O*NET physical abilities rating, classifying occupations with a score above the median as physically demanding occupations.[8]

In Table 3, we report the effect of robot exposure on the fraction of low-skilled workers whose occupations can be assigned physical abilities score employed in physically demanding occupations. There is evidence that the rise of robotic technology is associated with a lower share of low-skilled workers employed in physically demanding jobs: a ten percent increase in robots per 1,000 workers is associated with about 0.7 percentage points decrease in the fraction of low-skilled workers employed in physically demanding occupations. Evaluated at the sample mean, this estimate corresponds to a 1.2% decline. Although some of the estimates are imprecisely estimated, the results from the IV model suggest a larger magnitude of 2% reduction.

Another way to examine the reallocation of tasks in response to the rise in robotic technology is to analyze whether the fraction of low-skilled workers employed in risky jobs is affected by an increase in robot exposure. To do this, we first obtained the number of fatalities associated with each occupation from 2000 Census of Fatal Occupational Injuries (CFOI) and crosswalked it at the two-digit level to IPUMS

[7] The description for each ability is reported in Appendix Table 5.

[8] Appendix Table 6 reports the 10 most/least physically demanding occupations based on O*NET ratings in the sample.

consistent occupation codes. Then, we divide the number of fatalities with the number of workers employed in each occupation obtained from 2000 CPS ASEC to acquire the fatality rate corresponding to each occupation. Finally, we classify individuals working in occupations with a fatality rate above the median as being employed in high fatality risk jobs. It should be noted that this is not the only way to classify an individual as working in a risky job. For example, a person could be employed in an industry with a high injury rate. To explore this possibility, we obtained the injury rate associated with each industry from 2000 Survey of Occupational Injuries and Illnesses (SOII) and crosswalked it at the two-digit level to IPUMS consistent industry code (IND1990). Once again, we classify individuals working in industries with injury rate above the median as being employed in a high injury risk industry.[9]

The results of this exercise are reported in Table 4. Focusing on the IV estimates, there is evidence that the rise in robotic technology is negatively related with the share of low-skilled workers employed in risky jobs: a ten percent increase in robots per 1,000 workers is associated with approximately 0.3 and 0.2 percentage points decrease in the fraction of low-skilled workers employed in high fatality rate occupations and high injury rate, respectively. The magnitude of the effects is economically meaningful. Evaluated at the sample mean, these estimates correspond to about 9% and 4% reduction in the fraction of low-skilled workers employed in high fatality rate occupations and high injury rate industries.

[9]The fatality rate across occupations as well as the injury rate across industries are reported in Appendix Tables 7 and 8.

5.2 Changes in Unhealthy Behavior

Reallocation of tasks is not the sole mechanism through which the rise of robotic technology may affect health. Recent studies have documented evidence that mortality rate is pro-cyclical (Ruhm, 2000; Neumayer, 2004; Gerdtham and Ruhm, 2006), partly because of the reduction in unhealthy behaviors during recessions, such as smoking (Ruhm, 2005).[10] In this subsection, we examine whether there is evidence that a change in smoking behavior is one mechanism through which robot exposure affects health.

For this analysis, we obtain the CPS supplement on tobacco use from IPUMS. CPS tobacco use survey is not conducted every year; between 2004 and 2017, we have data for 2006, 2007, 2010, 2011, 2014, and 2015. In some survey years, CPS collected tobacco use information twice. In this case, we use both surveys and divide the survey weights by two to make the sample representative of the U.S. population. Similar to Ruhm (2005), we define current smokers as individuals who stated that they have smoked 100 or more cigarettes in their lifetime and who currently report smoking some days or every day. To construct additional measures of smoking behavior, we also use the information on whether an individual is an everyday smoker, and the average number of cigarettes currently smoked daily if the individual is an everyday smoker. Throughout this analysis, we focused on low-skilled population, whose labor market prospects are adversely affected by robot exposure (Acemoglu and Restrepo, 2020a; Graetz and Michaels, 2018; Giuntella and Wang, 2019) and whom the health outcomes are found to be improved by the rise of robotic

[10] Ruhm (2005) argues that reduction in job-related stress and increases in non-market leisure time incentivize individuals to adopt healthier lifestyle during recessions.

technology (Table 2).

The results of this exercise are reported in Table 5. We found no evidence that the rise in robotic technology has a statistically significant effect on the fraction of the low-skilled population identified as a current or everyday smoker. However, the IV estimates suggest that a ten percent increase in robots per 1,000 workers is associated with one fewer cigarettes per day among everyday smokers. Evaluated at the sample mean, these estimates correspond to about a 10% reduction in cigarettes per day among everyday smokers. These findings suggest that the effect of robot exposure on health that is coming through changing smoking behavior, if there is any, is likely to be the result of a reduction in the intensity of smoking.

6 Conclusion

The use of industrial robots has increased substantially in the United States. As such, there are interests in understanding more of how the rise of robotic technology will affect our behavior and our role in the economy. In this paper, we attempt to quantify the effect of robots on health. We hypothesize that higher penetration of industrial robots in a local economy will improve the health of low-skilled workers in the locality by nudging these workers toward occupations with lower intensity of physical tasks and by reducing unhealthy behaviors such as smoking.

We have reached a few main findings. First, we document evidence that higher penetration of industrial robots in the local labor market is positively related to the health status of low-skilled individuals. A ten percent increase in robots per 1,000 workers is associated with 0.5, 1.3, and 0.6 percentage points decline in the share of low-skilled population reporting poor health, work disability, and ever quit a job because of health reasons. Evaluated at the sample mean, these estimates correspond to an approximately 10% decrease in each of the outcomes. Second, we found that this effect is partly explained by the reallocation of tasks and a reduction in unhealthy behaviors. A ten percent increase in robots per 1,000 workers is associated with 2, 9, and 4 percent decline in the share of low-skilled workers employed in physically demanding occupations, occupations with high fatality rate, and industries with high injury rates respectively. We fail to find evidence that the fraction of the low-skilled population identified as a current or everyday smoker is affected by robot exposure. However, there is evidence that an increase in robot exposure is associated with a lower number of cigarettes per day consumed by an everyday smoker. This finding suggests that the effect of robot exposure on health that is coming through changing smoking behavior, if there is any, is likely to be the result of a reduction in smoking intensity.

7 Tables and Figures

Table 1: Summary Statistics

	Mean	SD	Min.	Max
Robots per 1,000 Workers	3.32	6.17	0.10	67.82
Fraction Black	0.13	0.10	0.00	0.56
Fraction Female	0.51	0.02	0.39	0.64
Unemployment Rate	0.07	0.04	0.00	0.29
Low-skilled				
Fraction Reporting Poor Health	0.05	0.04	0.00	0.32
Fraction Reporting Work Disability	0.14	0.07	0.00	0.71
Fraction Reporting Ever Quit for Health Reasons	0.05	0.04	0.00	0.42
High-skilled				
Fraction Reporting Poor Health	0.02	0.02	0.00	0.33
Fraction Reporting Work Disability	0.06	0.04	0.00	0.31
Fraction Reporting Ever Quit Job for Health Reasons	0.03	0.03	0.00	0.25

Notes: Estimates are based on International Federation of Robotics (IFR) data and Annual Social and Economic Supplement (ASEC) of the Current Population Survey obtained from IPUMS.

Table 2: The Effect of Robot Exposure on the Share of Population Reporting Poor Health Outcomes

	Poor Health		Work Disability		Ever Quit Job Because of Health Reasons	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A (Low-skilled)						
OLS: ln (Robot Exposure t-2)	-0.029*	-0.032**	-0.048*	-0.048*	-0.024*	-0.023
	(0.016)	(0.015)	(0.026)	(0.026)	(0.014)	(0.014)
2SLS: ln (Robot Exposure t-2)	-0.047*	-0.056**	-0.132**	-0.134**	-0.062*	-0.059*
	(0.027)	(0.027)	(0.065)	(0.066)	(0.032)	(0.033)
Mean of Dep. Var.	0.05	0.05	0.14	0.14	0.05	0.05
Panel B (High-skilled)						
OLS: ln (Robot Exposure t-2)	0.005	0.003	0.002	0.002	0.010	0.009
	(0.007)	(0.007)	(0.013)	(0.013)	(0.009)	(0.009)
2SLS: ln (Robot Exposure t-2)	0.025	0.022	-0.023	-0.023	-0.011	-0.012
	(0.016)	(0.016)	(0.021)	(0.021)	(0.015)	(0.015)
Mean of Dep. Var.	0.02	0.02	0.06	0.06	0.03	0.03
Controls:						
MSA and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Characteristics	No	Yes	No	Yes	No	Yes
Observations	1584	1584	1584	1584	1584	1584

Notes: Notes: The estimates show the effect of robot exposure on the share of population reporting poor health. Low-skilled is defined as individuals without a high school diploma. High-skilled is defined as individuals with at least a high school diploma. Control for MSA characteristics include population share of blacks, population share of female, and unemployment rate. The instrument in Panel B is constructed based on the number of operational robots in European countries. All regressions are weighted by MSA population in 2000. Standard errors clustered at the MSA level are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: The Effect of Robot Exposure on the Fraction of Low-skilled Workers Employed in Physically Demanding Occupations

	(1)	(2)
OLS: ln (Robot Exposure t-2)	-0.073**	-0.066*
	(0.035)	(0.034)
2SLS: ln (Robot Exposure t-2)	-0.115*	-0.102
	(0.067)	(0.068)
Mean of the Outcome Variable	0.58	0.58
Controls:		
MSA and Year Fixed Effects	Yes	Yes
MSA Characteristics	No	Yes
Observations	1584	1584

Notes: The estimates show the effect of robot exposure on the share of low-skilled workers reporting working in physically demanding occupations. Low-skilled is defined as individuals without a high school diploma. Control for MSA characteristics include population share of female, population share of blacks, and unemployment rate. The instrument in Panel B is constructed based on the number of operational robots in European countries. All regressions are weighted by MSA population in 2000. Standard errors clustered at the MSA level are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: The Effect of Robot Exposure on the Fraction of Low-skilled Workers Employed in Risky Jobs

	High Fatality Rate Occupations		High Injury Rate Industries	
	(1)	(2)	(3)	(4)
OLS: ln (Robot Exposure t-2)	-0.190***	-0.178**	-0.032	-0.026
	(0.072)	(0.073)	(0.081)	(0.082)
2SLS: ln (Robot Exposure t-2)	-0.296**	-0.277**	-0.217*	-0.232*
	(0.124)	(0.129)	(0.130)	(0.133)
Mean of the Outcome Variable	0.32	0.32	0.54	0.54
Controls:				
MSA and Year Fixed Effects	Yes	Yes	Yes	Yes
MSA Characteristics	No	Yes	No	Yes
Observations	1584	1584	1584	1584

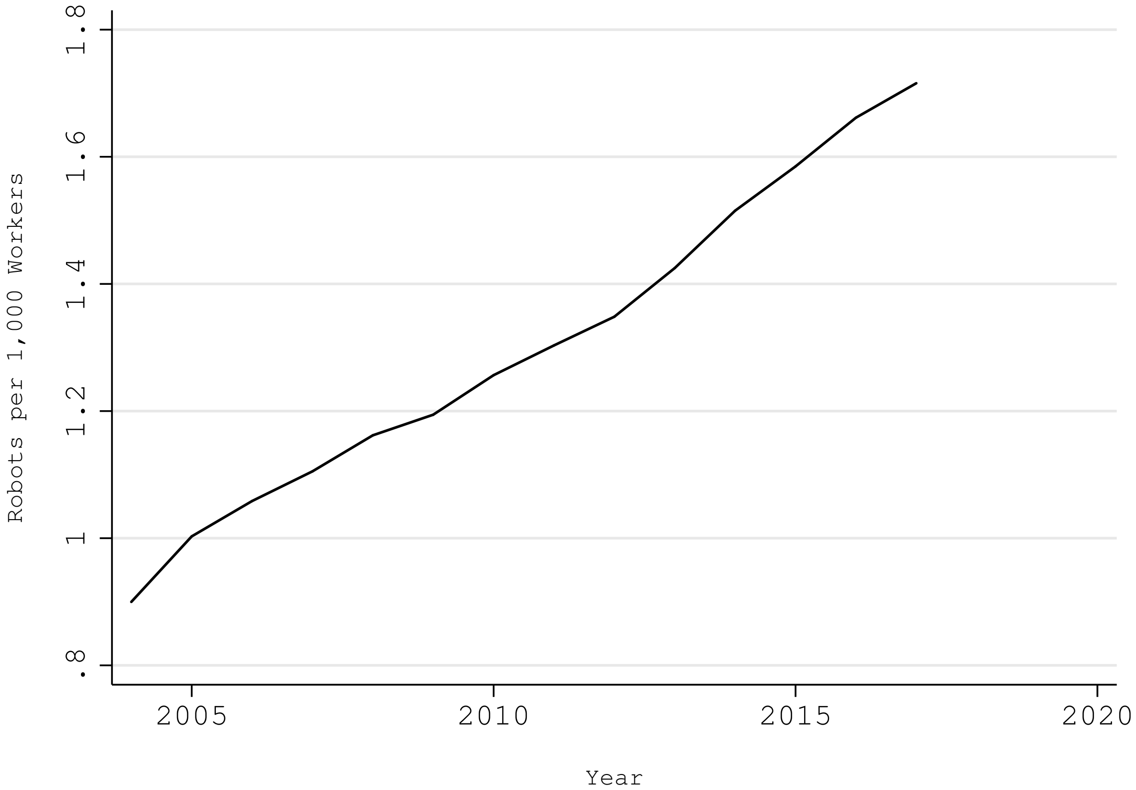
Notes: The estimates show the effect of robot exposure on the share of low-skilled workers employed in risky jobs. High fatality rate occupations are defined as occupations with fatality rate above median. High injury rate industries are defined as industries with injury rate above median. Low-skilled is defined as individuals without a high school diploma. Control for MSA characteristics include population share of blacks, population share of female, and unemployment rate. The instrument in Panel B is constructed based on the number of operational robots in European countries. All regressions are weighted by MSA population. Standard errors clustered at the MSA level are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Exposure to Robot and Smoking Behavior Among Low-skilled Population

	Fraction of Current Smoker		Fraction of Everyday Smoker		Cigs/Day (Everyday Smoker)	
	(1)	(2)	(3)	(4)	(5)	(6)
OLS: ln (Robot Exposure t-2)	0.056	0.052	0.051	0.047	0.892	0.873
	(0.056)	(0.056)	(0.042)	(0.041)	(1.659)	(1.614)
2SLS: ln (Robot Exposure t-2)	-0.007	-0.014	0.039	0.033	-9.561*	-9.581*
	(0.078)	(0.075)	(0.078)	(0.077)	(5.722)	(5.659)
Mean of Dep. Var.	0.24	0.24	0.19	0.19	10.43	10.43
Controls:						
MSA and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Characteristics	No	Yes	No	Yes	No	Yes
Observations	840	840	840	840	840	840

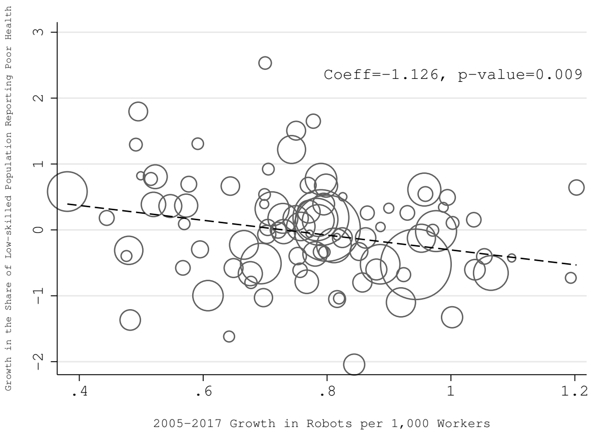
Notes: The estimates show the effect of robot exposure on the smoking behavior among low-skilled population. Low-skilled is defined as individuals without a high school diploma. Control for MSA characteristics include population share of female, population share of blacks, and unemployment rate. The instrument in Panel B is constructed based on the number of operational robots in European countries. All regressions are weighted by MSA population in 2000. Standard errors clustered at the MSA level are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 1: Rise of Robots in the United States

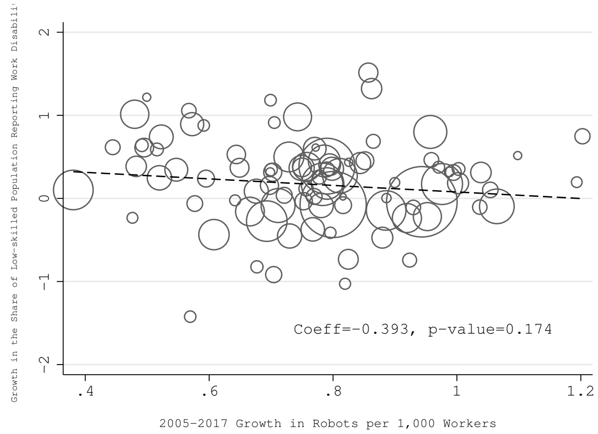


Notes: The estimates are based on IPUMS Annual Social and Economic Supplement of the Current Population Survey (CPS ASEC) and International Federation of Robotics (IFR) data.

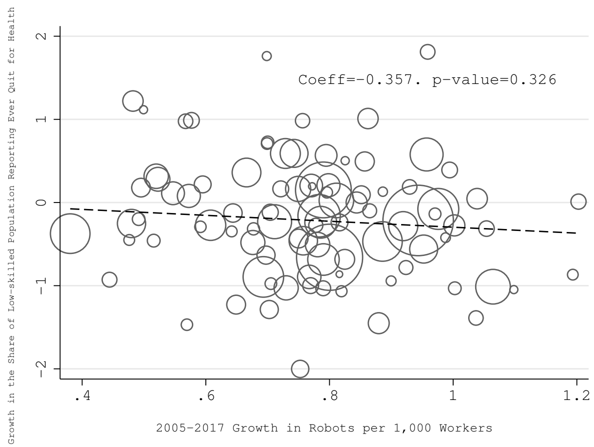
Figure 2: Robot Exposure and Health Outcomes (Low-skilled)



(a) Poor Health



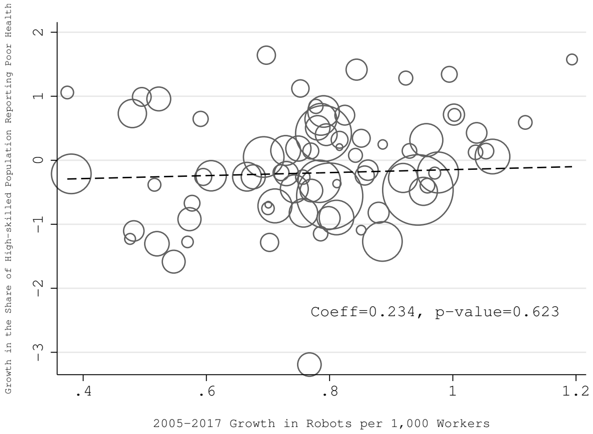
(b) Work Disability



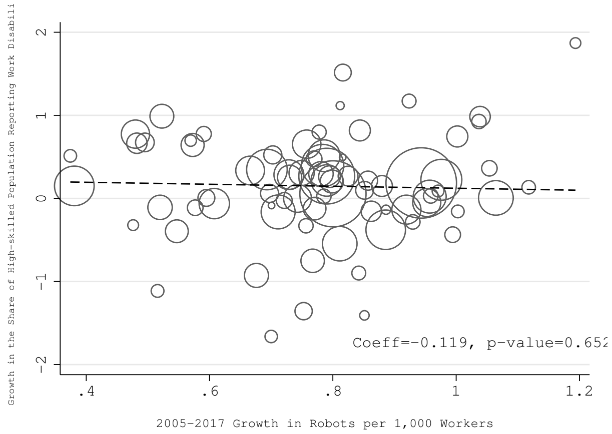
(c) Ever Quit for Health Reasons

Notes: Growth rates are calculated by taking first difference of natural log. The analysis uses 93 MSA in which the growth rates between 2005 and 2017 can be calculated. Size of the circle represents the weight assigned to that particular observation. Each observation is weighted by the commuting zone population in 2000. The growth in health outcomes are based on 2005 and 2017 IPUMS CPS-ASEC data. Robot exposure measure is constructed based on IPUMS 5% 1980 Census and 2005-2017 International Federation of Robotics (IFR) data.

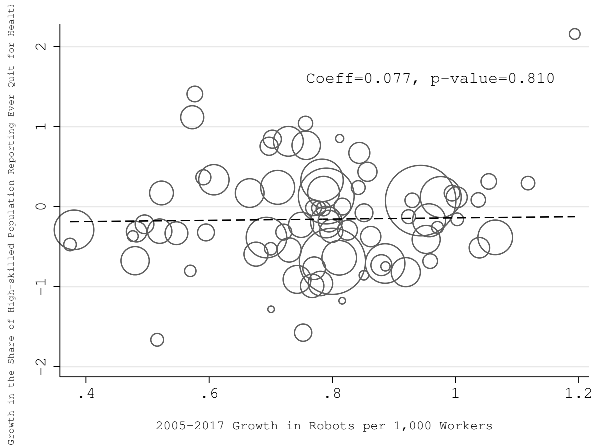
Figure 3: Robot Exposure and Health Outcomes (High-skilled)



(a) Poor Health



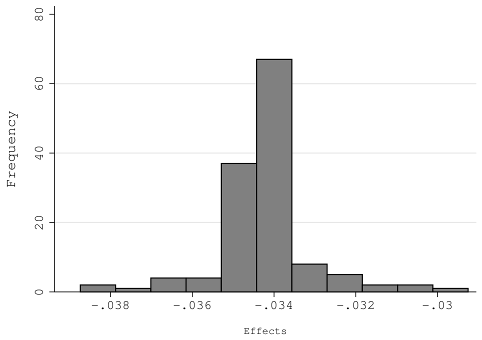
(b) Work Disability



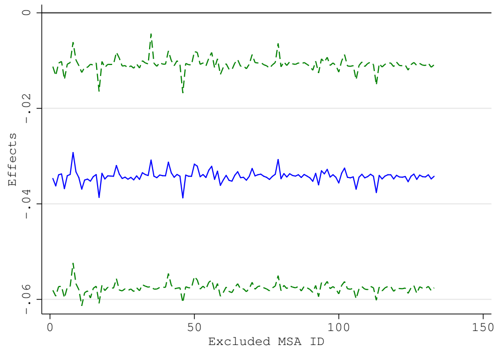
(c) Ever Quit for Health Reasons

Notes: Growth rates are calculated by taking first difference of natural log. The analysis uses 77 MSA in which the growth rates between 2005 and 2017 can be calculated. Size of the circle represents the weight assigned to that particular observation. Each observation is weighted by the commuting zone population in 2000. The growth in health outcomes are based on 2005 and 2017 IPUMS CPS-ASEC data. Robot exposure measure is constructed based on IPUMS 5% 1980 Census and 2005-2017 International Federation of Robotics (IFR) data.

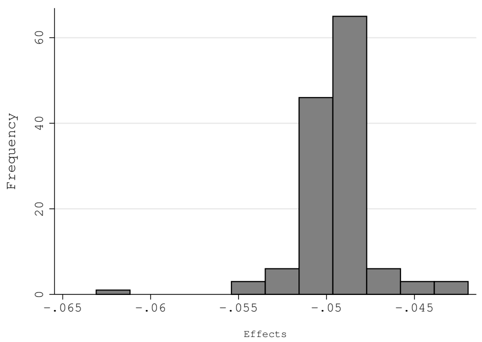
Figure 4: Robustness Check (Leave-one-out Test)



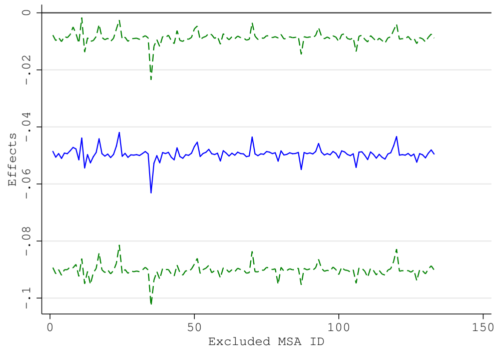
(a) Distribution of the Estimates (Poor Health)



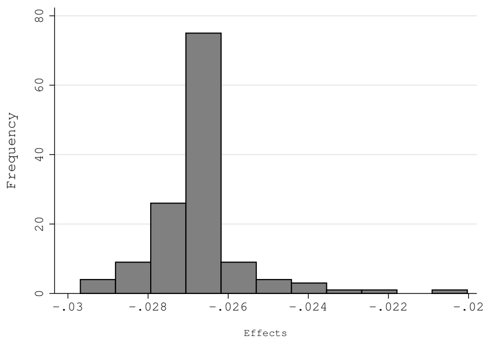
(b) Leave-one-out Test (Poor Health)



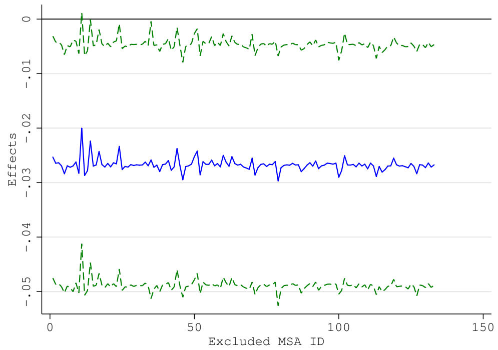
(c) Distribution of the Estimates (Work Dis.)



(d) Leave-one-out Test (Work Dis.)



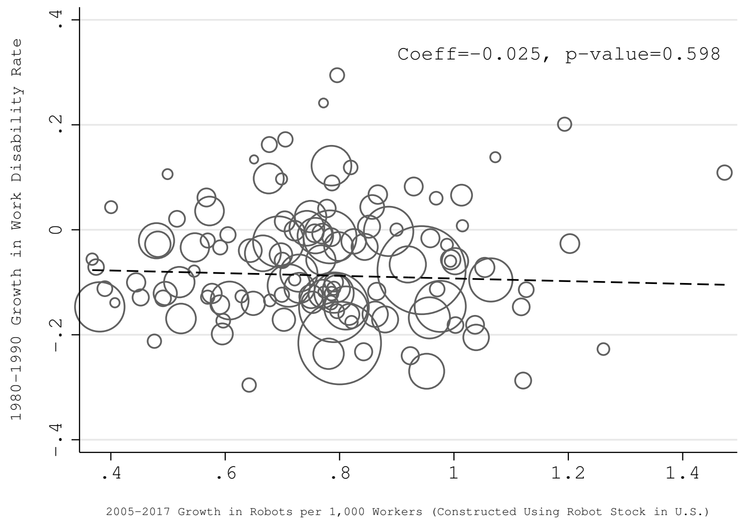
(e) Distribution of the Estimates (Quit)



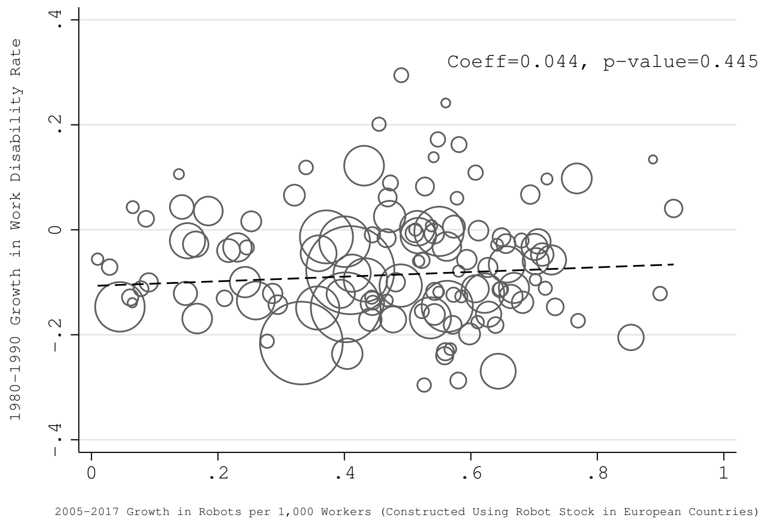
(f) Leave-one-out Test (Quit)

Notes: Subfigures on the left show the distribution of the estimates from the leave-one-out exercise. Subfigures on the right show the estimate of the effect when MSA ID in the corresponding x-axis is excluded from the regression. The blue line represents the coefficient estimates, while the green dash lines represent the 90% confidence interval constructed based on standard errors clustered at the MSA. All regressions are weighted by MSA population in 2000 and include controls for MSA and year fixed effects.

Figure 5: Robustness Check (Checking Pre-trends)



(a) Constructed Using Robot Stock in the U.S.



(b) Constructed Using Robot Stock in European Countries

Notes: Growth rates are calculated by taking first difference of natural log. The estimates for work disability rate among low-skilled workers are calculated based on 1980 and 1990 IPUMS 5% Census data. Robot exposure measure is constructed based on IPUMS 5% 1980 Census and 2005-2017 International Federation of Robotics (IFR) data. Size of the circle represents the weight assigned to that particular observation. Each observation is weighted by the MSA population.

References

Acemoglu, D. and Restrepo, P. (2020a). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Acemoglu, D. and Restrepo, P. (2020b). Unpacking skill bias: Automation and new tasks. Technical report, National Bureau of Economic Research.

Anelli, M., Giuntella, O., and Stella, L. (2019). Robots, labor markets, and family behavior.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333.

Coe, N. B. and Zamarro, G. (2011). Retirement effects on health in europe. *Journal of health economics*, 30(1):77–86.

Flood, S., King, M., Rodgers, R., Ruggles, S., and Warren, R. J. (2020). Integrated public use microdata series, current population survey: Version 7.0. *Minneapolis: University of Minnesota*.

Gerdtham, U.-G. and Ruhm, C. J. (2006). Deaths rise in good economic times: evidence from the oecd. *Economics & Human Biology*, 4(3):298–316.

Giuntella, O. and Wang, T. (2019). Is an army of robots marching on chinese jobs?

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2018). Bartik instruments: What, when, why, and how. Technical report, National Bureau of Economic Research.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American economic review*, 104(8):2509–26.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Granados, J. A. T. (2005). Recessions and mortality in spain, 1980–1997. *European Journal of Population / Revue européenne de Démographie*, 21(4):393–422.

Lin, S.-J. (2009). Economic fluctuations and health outcome: a panel analysis of asia-pacific countries. *Applied Economics*, 41(4):519–530.

Mazzonna, F. and Peracchi, F. (2012). Ageing, cognitive abilities and retirement. *European Economic Review*, 56(4):691–710.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ict polarized skill demand? evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, 96(1):60–77.

Neumayer, E. (2004). Recessions lower (some) mortality rates:: evidence from germany. *Social science & medicine*, 58(6):1037–1047.

Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly journal of economics*, 115(2):617–650.

Ruhm, C. J. (2005). Healthy living in hard times. *Journal of health economics*, 24(2):341–363.

Ruhm, C. J. (2015). Recessions, healthy no more? *Journal of health economics*, 42:17–28.

Ruhm, C. J. and Black, W. E. (2002). Does drinking really decrease in bad times? *Journal of health economics*, 21(4):659–678.

Staiger, D. O. and Stock, J. H. (1994). Instrumental variables regression with weak instruments. *National Bureau of Economic Research*.

Stevens, A. H., Miller, D. L., Page, M. E., and Filipski, M. (2015). The best of times, the worst of times: understanding pro-cyclical mortality. *American Economic Journal: Economic Policy*, 7(4):279–311.

Appendix

Appendix Table 1: Cities with Highest/Lowest Predicted Exposure to Robots in 2017

MSA Name	Predicted Robots/1000 Workers
Panel A: 10 Cities with Highest Predicted Robot Exposure	
Flint, MI	67.82
Detroit, MI	30.98
Lansing-East Lansing, MI	26.52
Saginaw-Bay City-Midland, MI	22.33
South Bend-Mishawaka, IN	21.73
Jackson, MI	19.40
Racine, WI	14.37
Fort Wayne, IN	13.99
Toledo, OH/MI	13.24
Ann Arbor, MI	12.87
Panel B: 10 Cities with Lowest Predicted Robot Exposure	
Laredo, TX	0.21
Austin, TX	0.39
Eugene-Springfield, OR	0.43
Fargo-Moorhead, ND/MN	0.43
Colorado Springs, CO	0.54
Columbus, GA/AL	0.56
Washington, DC/MD/VA	0.56
Pensacola, FL	0.56
Macon-Warner Robins, GA	0.58
Charleston-North Charleston, SC	0.58

Notes: The estimates are based on International Federation of Robotics (IFR) data. The number of workers in an industry is obtained from IPUMS 5% 1960 Census.

Appendix Table 2: Highest/Least Robot-Intensive Industries in 2017	
MSA Name	Robots/1000 Workers
Panel A: 5 Highest Robot-Intensive Industries	
Automotive	159.84
Electrical/Electronics	28.34
Plastic and Chemical Products	18.16
All Other Manufacturing Branches	11.64
Food Products and Beverage; Tobacco Products	6.56
Panel B: 5 Least Robot-Intensive Industries	
All Other non-Manufacturing Branches	0.01
Construction	0.05
Mining and Quarrying	0.07
Textiles, Leather, Wearing Apparel	0.09
Wood and Wood Products Including Furnitures	0.23

Notes: The estimates are based on International Federation of Robotics (IFR) data. The number of workers in an industry is obtained from IPUMS CPS ASEC 2017.

Appendix Table 3: First Stage Estimates		
	ln (US Robot Exposure t-2)	
	(1)	(2)
ln (EU Robot Exposure t-2)	0.497***	0.493***
	(0.096)	(0.095)
Robust F-Stats.	26.90	26.95
Controls:		
MSA and Year Fixed Effects	Yes	Yes
MSA Characteristics	No	Yes
Observations	1584	1584

Notes: The estimates are based on International Federation of Robots (IFR) data and Annual Social Economic Supplement (ASEC) of CPS from 2004 to 2015.

Appendix Table 4: Exposure to Robot and Share of Low-Skilled Population Reporting Poor Health Measures (Robustness – Lagged Effect Choice)

	Poor Health		Work Disability		Quit Job Because of Health Reasons	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A (Lagged One Year)						
OLS: ln (Robot Exposure t-1)	-0.030**	-0.033**	-0.058**	-0.057**	-0.014	-0.013
	(0.014)	(0.015)	(0.025)	(0.025)	(0.013)	(0.013)
2SLS: ln (Robot Exposure t-1)	-0.056**	-0.062***	-0.148**	-0.150**	-0.061**	-0.060*
	(0.024)	(0.024)	(0.062)	(0.062)	(0.030)	(0.031)
Observations	1716	1716	1716	1716	1716	1716
Panel B (Lagged Three Years)						
OLS: ln (Robot Exposure t-3)	-0.026	-0.031*	-0.047*	-0.048*	-0.022	-0.021
	(0.018)	(0.017)	(0.024)	(0.025)	(0.013)	(0.014)
2SLS: ln (Robot Exposure t-3)	-0.046	-0.055*	-0.120**	-0.122**	-0.049*	-0.047
	(0.031)	(0.031)	(0.060)	(0.062)	(0.028)	(0.030)
Observations	1452	1452	1452	1452	1452	1452
Controls:						
MSA and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Characteristics	No	Yes	No	Yes	No	Yes

Notes: Notes: The estimates show the effect of robot exposure on the share of population reporting poor health. Low-skilled is defined as individuals without a high school diploma. High-skilled is defined as individuals with at least a high school diploma. Control for MSA characteristics include population share of blacks, population share of female, and unemployment rate. The instrument in Panel B is constructed based on the number of operational robots in European countries. All regressions are weighted by MSA population in 2000. Standard errors clustered at the MSA level are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Appendix Table 5: O*NET Physical Abilities

Ability	Description
Dynamic Flexibility	The ability to quickly and repeatedly bend, stretch, twist, or reach out with your body, arms, and/or legs.
Dynamic Strength	The ability to exert muscle force repeatedly or continuously over time.
Explosive Strength	The ability to use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object
Extent Flexibility	The ability to bend, stretch, twist, or reach with your body, arms, and/or legs.
Gross Body Coordination	The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.
Gross Body Equilibrium	The ability to keep or regain your body balance or stay upright when in an unstable position.
Stamina	The ability to exert yourself physically over long periods of time without getting winded or out of breath.
Static Strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.
Trunk Strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without ’giving out’ or fatiguing.

Appendix Table 6: Most/Least Physically Demanding Occupations	
	ONET Score
Panel A: 10 Most Physically Demanding Occupations	
Dancers	67.39
Roofers and Slaters	52.56
Plasterers	47.67
Concrete and Cement Workers	46.94
Millwrights	46.33
Recreation Workers	46.11
Structural Metal Workers	45.81
Masons, Tilers, and Carpet Installers	45.40
Helpers, Constructions	44.33
Carpenters	44.28
Panel B: 10 Least Physically Demanding Occupations	
Chief Executives and Public Administrators	0.17
Technical Writers	0.33
Metallurgical and Materials Engineers, Variously Phrased	0.33
Sales Engineers	0.33
Record Clerks	0.33
Urban and Regional Planners	0.33
Financial Managers	0.33
Interviewers, Enumerators, and Surveyors	0.44
Physicists and Astronomers	0.50
Architects	0.67

Notes: The estimates are based on ONET data. ONET score shows the importance of physical abilities in a given occupation on a standardized scale ranging from 0 (min) to 100 (max).

Appendix Table 7: Fatality Rates Across Occupation

Occupation Title	Fatalities per 100,000 Workers	IPUMS OCC1990 Codes
Managerial and Professional Specialty		
Executive, Administrative, and Managerial	2.00	occ1990>=3 & occ1990<=37
Professional Specialty	1.19	occ1990>=43 & occ1990<=200
Technical, Sales, and Administrative Support		
Technicians and Related Support Occupations	4.40	occ1990>=203 & occ1990<=235
Sales Occupations	2.38	occ1990>=243 & occ1990<=290
Admin. Support Occupations, including clerical	0.54	occ1990>=303 & occ1990<=391
Service Occupations		
Private Household Service Occupations	0.32	occ1990>=405 & occ1990<=408
Protective Service Occupations	10.57	occ1990>=415 & occ1990<=427
Service Occupations, except protective and household	1.16	occ1990>=434 & occ1990<=469
Farming, Forestry, and Fishing		
Farming Operators and Managers	29.38	occ1990>=473 & occ1990<=476
Other Agricultural and Related Occupations	15.87	occ1990>=479 & occ1990<=489
Forestry and Logging Occupations	109.32	occ1990==496
Fishers, Hunters, and Trappers	104.79	occ1990==498
Precision Production, Craft, and Repair		
Mechanics and Repairers	6.94	occ1990>=505 & occ1990<=549
Construction Trades	10.62	occ1990>=558 & occ1990<=599
Extractive Occupations	93.32	occ1990>=614 & occ1990<=617
Precision Production Occupations	3.01	occ1990>=628 & occ1990<=699
Operators, Fabricators, and Laborers		
Machine Operators, Assemblers, and Inspectors	3.05	occ1990>=703 & occ1990<=799
Transportation and Material Moving Occupations	23.89	occ1990>=803 & occ1990<=859
Handlers, Equipment Cleaners, Helpers, and Laborers	11.52	occ1990>=865 & occ1990<=890

Notes: The estimates are obtained based on the data published in 2000 Census of Fatal Occupational Injuries (CFOI). CFOI statistics only report the total number of fatalities by industries. To obtain fatality rate in an industry, we divide the total number of fatalities by the number of workers employed in the industry obtained from 2000 CPS and multiply it with 100,000.

Appendix Table 8: Injury Rates Across Industries

Industry Title	Injuries/Illnesses per 100 Workers	IPUMS IND1990 Codes
Agriculture, Forestry, and Fishing		
Agricultural Production (Crops)	6.70	ind1990==10
Agricultural Production (Livestock)	10.40	ind1990==11
Agricultural Services	6.80	ind1990>=20 & ind1990<=30
Forestry	8.80	ind1990==31
Fishing, Hunting, and Trapping	6.70	ind1990==32
Mining		
Metal Mining	4.90	ind1990==40
Coal Mining	7.50	ind1990==41
Oil and Gas Extraction	4.20	ind1990==42
Nonmetallic Minerals, except fuels	4.30	ind1990==50
Construction	8.30	ind1990==60
Manufacturing		
Food and Kindred Products	12.40	ind1990>=100 & ind1990<=122
Tobacco	6.20	ind1990==130
Textile Mill Products	6.00	ind1990>=132 & ind1990<=150
Apparel and Other Textile Products	6.10	ind1990>=151 & ind1990<=152
Paper and Allied Products	6.50	ind1990>=160 & ind1990<=162
Printing and Publishing	5.10	ind1990>=171 & ind1990<=172
Chemical and Allied Products	4.20	ind1990>=180 & ind1990<=192
Petroleum and Coal Products	3.70	ind1990>=200 & ind1990<=201
Rubber and Misc. Plastics	10.70	ind1990>=210 & ind1990<=212
Leather and Leather Products	9.00	ind1990>=220 & ind1990<=222
Lumber and Wood Products	12.10	ind1990>=230 & ind1990<=241
Furniture and Fixtures	11.20	ind1990==242
Stone, Clay, and Glass Products	10.40	ind1990>=250 & ind1990<=262
Primary Metal Industries	12.60	ind1990>=270 & ind1990<=280
Fabricated Metal Products	11.90	ind1990>=281 & ind1990<=301
Industrial Machinery and Equipment	8.20	ind1990>=310 & ind1990<=332
Electronic and Other Electric Equipment	5.70	ind1990>=340 & ind1990<=350
Transportation Equipment	13.70	ind1990>=351 & ind1990<=370
Instruments and Related Products	4.50	ind1990>=371 & ind1990<=381
Misc. Manufacturing Industries	7.20	ind1990>=390 & ind1990<=392
Transportation and Public Utilities		
Railroad Transportation	3.60	ind1990==400
Local and Interurban Passenger Transit	8.00	ind1990>=401 & ind1990<=402
Trucking and Warehousing	7.90	ind1990>=410 & ind1990<=412
Water Transportation	7.00	ind1990==420
Transportation by Air	13.90	ind1990==421
Transportation Services	3.20	ind1990>=422 & ind1990<=432
Communications	2.60	ind1990>=440 & ind1990<=442
Electric, Gas, and Sanitary Services	6.30	ind1990>=450 & ind1990<=472
Wholesale Trade		
Durable Goods	5.10	ind1990>=500 & ind1990<=532
Non-durable Goods	6.90	ind1990>=540 & ind1990<=571
Retail Trade		
Building Materials and Garden Supplies	8.20	ind1990>=580 & ind1990<=590
General Merchandise Stores	5.90	ind1990>=591 & ind1990<=600
Food Stores	8.00	ind1990>=601 & ind1990<=611
Automotive Dealers and Service Stations	5.60	ind1990>=612 & ind1990<=622
Apparel and Accessory Stores	3.70	ind1990>=623 & ind1990<=630
Furniture and Homefurnishings Stores	4.70	ind1990>=631 & ind1990<=640
Eating and Drinking Places	5.30	ind1990==641
Miscellaneous Retail	3.90	ind1990>=642 & ind1990<=691

Continued – Appendix Table 8: Injury Rates Across Industries

Industry Title	Injuries/Illnesses per 100 Workers	IPUMS IND1990 Codes
Finance, Insurance, and Real Estate		
Depository Institutions	1.40	ind1990>=700 & ind1990<=701
Non-depository Institutions	1.10	ind1990==702
Security and Commodity Brokers	0.60	ind1990==710
Insurance Carriers	1.00	ind1990==711
Real Estate	4.10	ind1990==712
Services		
Business Services	3.20	ind1990>=721 & ind1990<=741
Auto Repair, Services, and Parking	5.00	ind1990>=742 & ind1990<=751
Misc. Repair Services	4.90	ind1990>=752 & ind1990<=760
Hotels and Other Lodging Places	6.90	ind1990>=762 & ind1990<=770
Personal Services	3.30	ind1990==761, (ind1990>=771 & ind1990<=791)
Motion Pictures	3.40	ind1990>=800 & ind1990<=801
Amusement and Recreation Services	6.90	ind1990>=802 & ind1990<=810
Health Services	7.40	ind1990>=812 & ind1990<=840
Legal Services	0.70	ind1990==841
Educational Services	3.20	ind1990>=842 & ind1990<=861
Social Services	6.10	ind1990>=862 & ind1990<=871
Museums, Botanical, Zoological Gardens	5.20	ind1990==872
Membership Organizations	3.00	ind1990>=873 & ind1990<=881
Engineering and Management Services	1.70	ind1990>=882 & ind1990<=893
Public Administration	3.20	ind1990>=900 & ind1990<=932

Notes: The injury rates are obtained from 2000 Survey of Occupational Injuries and Illnesses (SOII). SOII incidence rates represent the number of injuries and illnesses per 100 full-time workers.