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Does the rise of robotic technology make people healthier?

Christian Gunadi[1] [iD] | Hanbyul Ryu[2]

[1]Herbert Wertheim School of Public Health and Human Longevity Science, University of California San Diego, San Diego, California, USA

[2]Hanyang University (ERICA Campus), College of Business and Economics, Ansan-si, South Korea

Correspondence
Christian Gunadi, Herbert Wertheim School of Public Health and Human Longevity Science, University of California San Diego, San Diego, CA 92093, USA.
Email: cgunadi@health.ucsd.edu

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. Using the variation in the initial distribution of industrial employment in US cities and the difference in robot adoption across industries over time to predict robot exposure at the local labor market, we find evidence that higher penetration of industrial robots in the local economy is positively related to the health of the low-skilled population. A 10% increase in robots per 1000 workers is associated with an approximately 10% reduction in the share of low-skilled individuals reporting poor health. Further analysis suggests that the reallocation of tasks partly explains this finding. A 10% increase in robots per 1000 workers is associated with an approximately 1.5% reduction in physical tasks supplied by low-skilled workers.

KEYWORDS
automation, health, occupational injury, robots

JEL CLASSIFICATION
I10, I13, J24, O33

1 | INTRODUCTION

It is hard to not overstate the importance of good health in our life. Our productivity at work depends on our health (Alavinia et al., 2009; Meerding et al., 2005; Schultz & Edington, 2007). This, in turn, affects our income (Strauss & Thomas, 1998). Perhaps more importantly, our happiness and satisfaction in life depend on our health (Angner et al., 2013, 2009). It is unsurprising, therefore, to see many researchers are interested in finding out the determinants of good health (e.g., Grossman, 1972, 2000; Grossman & Kaestner, 1997).

In this paper, we attempt to contribute to the literature examining the determinants of health by proposing that the rise of robotic technology can influence our health. We hypothesize that higher penetration of robots in a local labor market could improve the health of low-skilled individuals in the locality by substituting repetitive, manual tasks usually done by low-skilled workers, nudging these workers towards occupations with lower intensity of physical tasks, improving their health.[1] Indeed, workers in industries that require manual labor are typically more exposed to higher health and safety risks than those performing desk or professional work. Robots have the potential to enhance work conditions for the former type of workers by taking away some repetitive, and potentially dangerous, tasks that humans do as long as it is maintained properly. Supporting this possibility, Figure 1 shows that in the period that robot use has increased, there has been a steady decrease in occupational injury or illness probabilities. Occupational safety and
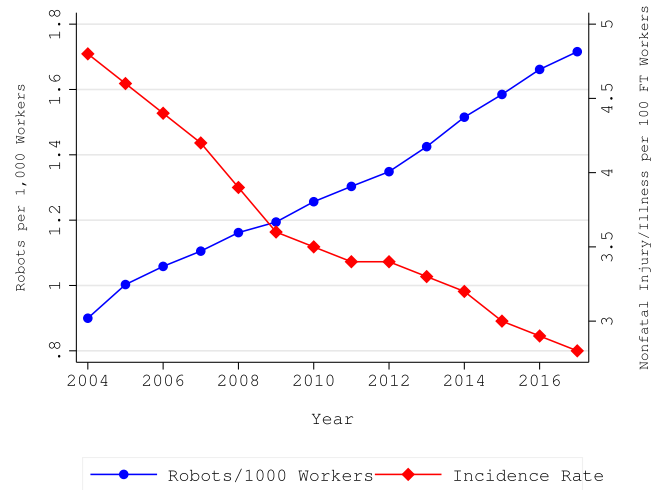
FIGURE 1 Rise of robotic technology and occupational injury in the United States. Robots per 1000 workers are estimated based on IPUMS Annual Social and Economic Supplement of the Current Population Survey (CPS ASEC) and International Federation of Robotics (IFR) data. Nonfatal occupational injury and illness incidence rate in private industry is obtained from US Bureau of Labor Statistics

health were surely affected in this period by multiple factors such as changes in safety regulations and improvement of safety equipment, but increased use of robots could also be a significant factor contributing to the reduction of workplace injury.

To test our hypothesis, we begin by examining the relationship between the rise of robotic technology and health. Using the variation in the initial distribution of industrial employment in US cities and the difference in robot adoption across industries over time to predict robot exposure at the local labor market, we find evidence that higher exposure to robots is positively related to the health of the low-skilled population. A 10% increase in robots per 1000 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. Separating the analysis by gender, the evidence shows that the health effects of robots are mainly concentrated among men. Examining the mechanisms behind these findings, we find evidence of the reallocation of tasks. A 10% increase in robots per 1000 workers is associated with an approximately 1.5% reduction in physical tasks and tasks with a high injury rate supplied by low-skilled workers.[2]

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 US commuting zones, Acemoglu and Restrepo (2020) 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.[3] 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 socioeconomic outcomes. We believe this is important since the rise of robotic technology is likely to bring wider implications beyond the labor market. For example, the work by Anelli et al. (2019) found that higher adoption of robots in the local labor market affects 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. A closely related study to our paper is the work by Gihleb et al. (2020). Conducted independently and at the same time as our paper, the authors found that an increase in robot exposure is associated with a reduction in work-related injuries in the United States. Our paper complements the findings in Gihleb et al. (2020) in a few main ways. First, we examine directly the relationship between robot exposure and health, showing evidence that a higher industrial robots adoption in the US cities is associated with an improvement in the health status of low-skilled individuals.[4] That is, reduction in work-related injuries, which is the focus in Gihleb et al. (2020), is a mechanism through which a rise in robot exposure can affect health. In addition, we use different data and econometric specifications to examine the potential reallocation of tasks due to the rise in robot exposure.[5]

The rest of the article is constructed as follows. The next section examines the effects of robots on health, detailing the data used in the analysis as well as the identification strategy, and documents the findings. Section 3 explores the potential mechanisms of how robots may affect health. Section 4 concludes.

2 | THE EFFECTS OF ROBOTS ON HEALTH

2.1 | Data and descriptive statistics

2.1.1 | International Federation of Robotics 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 & Restrepo, 2020; Giuntella & Wang, 2019; Graetz & Michaels, 2018), we use the variation in the initial distribution of industrial employment in US cities 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.[6] In addition, not all robots are classified into one of the IFR industry classifications. 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 metropolitan statistical area (MSA) (i.e., city) 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 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 1000 workers across the cities in our sample (Table 1). Many of the cities with the highest predicted robot exposure are located in the Midwest (Table A1). This is unsurprising since the automotive industry, which is the top robot-intensive industry (Table A2), is mainly concentrated in this region.

2.1.2 | 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 US 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 from the age of 18–64 to avoid potential bias associated with changes in perceived/actual health after retirement (Coe & Zamarro, 2011; Mazzonna & Peracchi, 2012).

	Mean	SD	Min	Max
Robots per 1000 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
Fraction low-skilled (high school diploma or less)	0.39	0.09	0.07	0.75
Fraction high-skilled (at least some college exp.)	0.61	0.09	0.25	0.93
Fraction with some college experience only	0.29	0.06	0.09	0.53
Fraction with at least a Bachelor's degree	0.32	0.10	0.06	0.77
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 for health reasons	0.03	0.03	0.00	0.25

TABLE 1 Cities' descriptive statistics

Note: Estimates are based on 2006–2017 International Federation of Robotics (IFR) data and Annual Social and Economic Supplement (ASEC) of the Current Population Survey obtained from IPUMS. There are 1739 city × year observations in the sample.

The health status in March CPS indicates an individual's health on a 5-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.[7] 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 the low-skilled population with no high school diploma reporting poor health is higher than their high-skilled counterparts: 5% of the low-skilled population reports that they are in poor health, while only 2% of the high-skilled population with at least a high school diploma reports that they are in poor health (Table 1).[8] 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.

2.2 | Empirical methodology

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

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

where y_{ct} is the outcome for 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 an increase of 1 in the natural log of robots per 1000 workers. We (natural) log-transformed the robot exposure measure to take into account that the effect of robots is unlikely to be linear. That is, the effect magnitude of increasing robots per 1000 workers by 1 in a place where there is only 1 robot per 1000 workers is likely to be different from a place where there are 100 robots per 1000 workers. Additionally, the robot exposure measure is highly skewed (Figure A1). Although it is always larger than zero, only a few city × year

observations have a value larger than 20. The log transformation will help to make the robot exposure measure to be more normally distributed. We lagged the effects since it should take some time for individuals to adjust to an increase in robot exposure.[9] X_{ct} is a vector of city-level control variables which include the population share of Blacks, the population share of Hispanics, the population share of females, and the unemployment rate. δ_c and δ_t are MSA and year fixed effects, respectively. The period of the analysis is 2006–2017. Year 2006 is the start year because the effects of robot exposure are lagged by 2 years and the earliest robot by industry data is only available starting from 2004. Year 2017 is the end year because the latest IFR data that we can obtain is 2017. We include all MSA in IPUMS 5% 1960 Census that can be identified in March CPS between 2006 and 2017 in our analysis. There are 1739 city × year observations in our main sample. All regressions are weighted by the MSA population in 2000.

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 (2020) 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 US 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.[10]

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 (Table A3). 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 1% 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 US cities. Second, the instrument must not be correlated with unobserved local factors affecting the health of individuals in US localities. Although this condition is essentially untestable, we will provide supporting evidence that this condition is fulfilled in the next section.

2.3 | Results

2.3.1 | Main findings

Before reporting the results from our main empirical specifications, we present 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 a high school diploma or less, while high-skilled is defined as those with at least some college experiences. This is based on our hypothesis that robots mainly substitute for routine, manual-intensive tasks that were usually done by the low-skilled workers, nudging these workers towards occupations that are less physically demanding.[11] 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 1000 workers between 2006 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 1% increase in robot exposure is associated with a 1.17% decline in the fraction of the low-skilled population reporting poor health. We also see there is a negative relationship between the growth of robots per 1000 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 (Figure 2b,c).

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 the estimate is small in magnitude and not statistically significant (Figure 3a). Qualitatively similar findings are found for the share of high-skilled population reporting work disability and ever quit a job because of health reasons (Figure 3b,c).

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 10% increase in robots per 1000 workers is
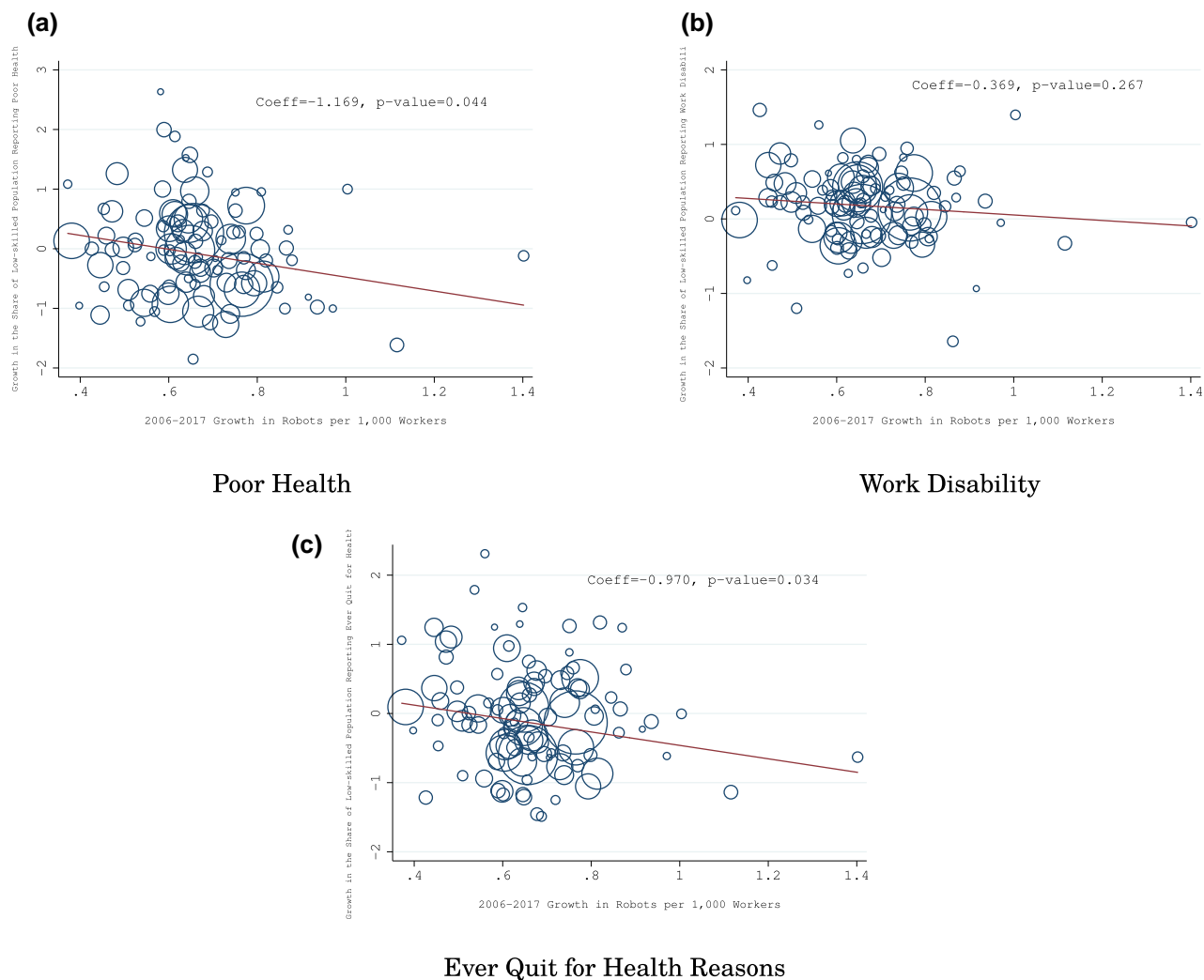
(a)

Poor Health

(b)

Work Disability

(c)

Ever Quit for Health Reasons

FIGURE 2   Robot exposure and health outcomes (low-skilled). Growth rates are calculated by taking first difference of natural log. The analysis uses 105 MSA in which the growth rates between 2006 and 2017 can be calculated. Size of the circle represents the weight assigned to that particular observation. Each observation is weighted by the MSA population in 2000. The growth in health outcomes are based on 2006 and 2017 IPUMS CPS-ASEC data. Robot exposure measure is constructed based on IPUMS 5% 1960 Census and 2006–2017 International Federation of Robotics (IFR) data. MSA, metropolitan statistical area

associated with about 0.3 percentage point decrease in the share of low-skilled population reporting poor health (Column 1 of Panel A).[12] The results from the IV model suggest that this estimate underestimates the magnitude of the effect (−0.41p.p.).[13] Evaluated at the sample mean, this estimate corresponds to about a 10% decline. Qualitatively similar findings are found for the other health outcomes: a 10% 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.[14]

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 1000 workers, we can rule out an effect size larger than a 3.5% 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.[15]

Extending the analysis, we examine the effects separately by gender (Table 3). We found that the health effects of robots among the low-skilled population are mainly driven by men. Focusing on the IV estimates, a 10% increase in robot exposure is associated with a 1.8p.p. and 0.8p.p. decline in the share of low-skilled men reporting work disability and ever quit a job because of health reasons. For women, the corresponding effects are much lower at 0.8p.p. and 0.3p.p., respectively.
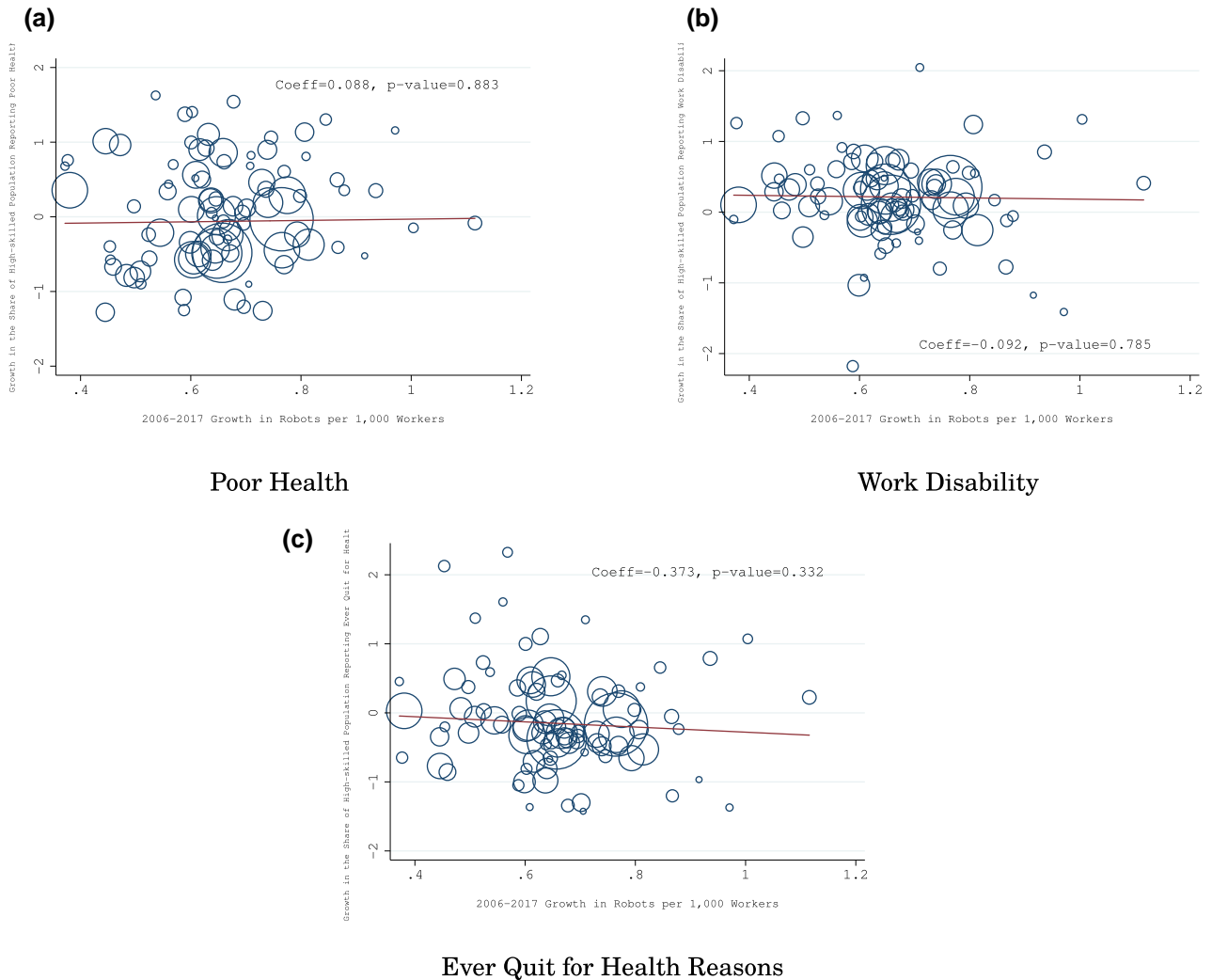
FIGURE 3 Robot exposure and health outcomes (high-skilled). Growth rates are calculated by taking first difference of natural log. The analysis uses 90 MSA in which the growth rates between 2006 and 2017 can be calculated. Size of the circle represents the weight assigned to that particular observation. Each observation is weighted by the MSA population in 2000. The growth in health outcomes are based on 2006 and 2017 IPUMS CPS-ASEC data. Robot exposure measure is constructed based on IPUMS 5% 1960 Census and 2006–2017 International Federation of Robotics (IFR) data. MSA, metropolitan statistical area

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 the low-skilled population reporting poor health. Separating the analysis by gender, we found that the health effects of robots are concentrated among low-skilled men. We check the robustness of this finding in the next subsection.

2.3.2 | Robustness checks

In the main empirical specifications, we choose to measure the 2-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 1- or 3-year lagged robot exposures are used in the analysis (Table A5). The results of this exercise are largely in line with the findings from the main empirical specifications.

So far, our focus has been on individuals from the age of 18–64. As a robustness check, we also report the results of the analysis when we use different age intervals (25–60- and 25–64-year-olds) in Table A6. The findings are virtually unaffected.

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)	−0.026**	−0.028**	−0.042**	−0.039**	−0.021*	−0.019*
	(0.013)	(0.013)	(0.018)	(0.018)	(0.011)	(0.011)
2SLS: ln (Robot exposure t-2)	−0.041*	−0.047**	−0.133***	−0.133**	−0.058**	−0.057**
	(0.024)	(0.024)	(0.051)	(0.052)	(0.026)	(0.026)
Mean of Dep. Var.	0.05	0.05	0.13	0.13	0.05	0.05
Panel B (high-skilled)						
OLS: ln (Robot exposure t-2)	0.003	0.002	0.004	0.004	0.007	0.007
	(0.006)	(0.006)	(0.012)	(0.012)	(0.009)	(0.009)
2SLS: ln (Robot exposure t-2)	0.015	0.013	−0.021	−0.021	−0.012	−0.013
	(0.013)	(0.013)	(0.018)	(0.018)	(0.014)	(0.014)
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	1739	1739	1739	1739	1739	1739

Note: The estimates show the effect of robot exposure on the share of population reporting poor health. Low-skilled is defined as individuals with a high school diploma or less. High-skilled is defined as individuals with at least some college experiences. Control for MSA characteristics include population share of Blacks, population share of Hispanics, population share of female, and unemployment rate. The instrument in 2SLS model 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.

Abbreviation: MSA, metropolitan statistical area.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

One concern is that individuals may migrate out of the city in response to an increase in robot exposure. The sign of the bias in this case depends on the characteristics of individuals migrating out of the city. If individuals with poor health outcomes are migrating out of the city in response to higher exposure to robots, the estimates will be biased toward findings showing that an increase in robots per 1000 workers improves the health of the population. However, if the healthier individuals are more likely to move in response to higher robot exposure, the estimates will be biased toward findings showing that an increase in robots per 1000 workers worsens the health of the population. One way to address this concern is to focus the analysis on nonmovers (Table A7).[16] The results from focusing on nonmovers largely support the main findings.

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 −0.026 and −0.036 (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.

The work by Goldsmith-Pinkham et al. (2020) 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

TABLE 3 The effect of robot exposure on the share of low-skilled population reporting poor health outcomes by gender

	Poor health		Work disability		Ever quit job because of health reasons	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A (male)						
OLS: ln (Robot exposure t-2)	−0.022	−0.024*	−0.047**	−0.045**	−0.032***	−0.030***
	(0.014)	(0.014)	(0.020)	(0.020)	(0.012)	(0.011)
2SLS: ln (Robot exposure t-2)	−0.045*	−0.051**	−0.181**	−0.181**	−0.086***	−0.084***
	(0.025)	(0.025)	(0.072)	(0.074)	(0.031)	(0.031)
Mean of Dep. Var.	0.05	0.05	0.13	0.13	0.05	0.05
Panel B (female)						
OLS: ln (Robot exposure t-2)	−0.035**	−0.036**	−0.038	−0.034	−0.011	−0.010
	(0.017)	(0.017)	(0.023)	(0.024)	(0.016)	(0.017)
2SLS: ln (Robot exposure t-2)	−0.040	−0.046	−0.078*	−0.077	−0.028	−0.029
	(0.032)	(0.032)	(0.046)	(0.048)	(0.033)	(0.034)
Mean of Dep. Var.	0.05	0.05	0.13	0.13	0.05	0.05
Controls						
MSA and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA characteristics	No	Yes	No	Yes	No	Yes
Observations	1739	1739	1739	1739	1739	1739

Note: The estimates show the effect of robot exposure on the share of population reporting poor health. Low-skilled is defined as individuals with a high school diploma or less. Control for MSA characteristics include population share of Blacks, population share of Hispanics, population share of female, and unemployment rate. The instrument in 2SLS model is constructed based on the number of operational robots in European countries. The number of observations in Panel C is slightly lower because there are three city × year observations in which no low-skilled female workers are observed All regressions are weighted by MSA population in 2000. Standard errors clustered at the MSA level are reported in parentheses.

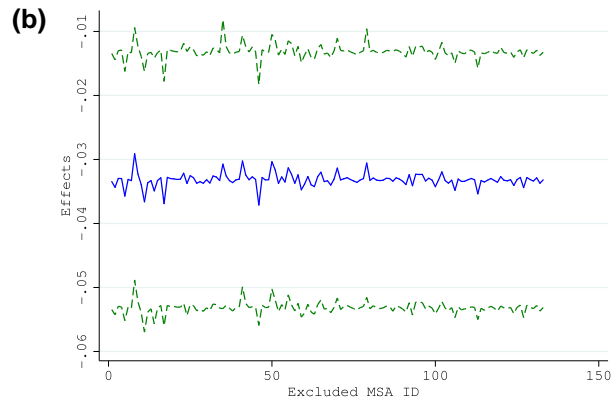Abbreviation: MSA, metropolitan statistical area.

*p < 0.1.

**p < 0.05.

***p < 0.01.

proxy for the exposure to the shock. Cities that rely more on robot-intensive industries will be more exposed to the shock.[17] In this case, the assumption for the estimates to be valid is that cities that were experiencing high growth of robot per 1000 workers in 2006–2017 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 2006–2017 growth of robots per 1000 workers and the 1980–1990 growth of the low-skilled population reporting work disability.[18] The slope of the fitted lines suggests that a 10% increase in robot exposure between 2006 and 2017 is associated with a 1.5% decline in the share of low-skilled population reporting work disability (Figure 5a), suggesting that the work disability rate in cities that are experiencing rapid growth of robots follows a different pretrend than those that have low growth of robots per 1000 workers. Although this is a potential concern, it is worth noting that our identification strategy relies on using the variation of robots' intensity across industries in the European countries as an instrument. Figure 5b reports the result when we use the robot stock in European countries to construct the measure of robot exposure. The magnitude of the estimate is small (−0.059) and not statistically significantly different from zero, supporting the validity of the estimates obtained using the IV model.[19]
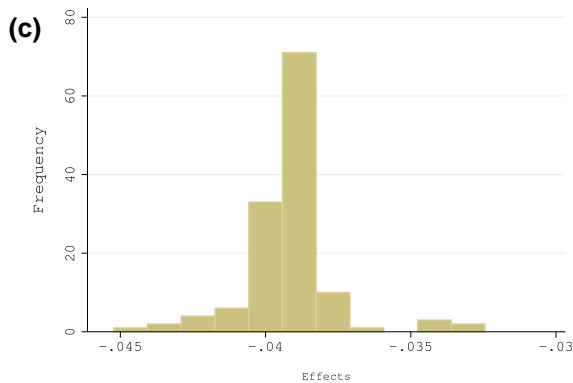
As an additional robustness check, we estimate a model with region (census division)—by-year fixed effects. Cities in different regions may follow different trends in health outcomes due to unobserved factors that vary across regions over time, and adding region-by-year fixed effects will control for these potential confounding factors. The results of this exercise are reported in Table A9. Although the estimates become imprecise, the findings hold qualitatively.
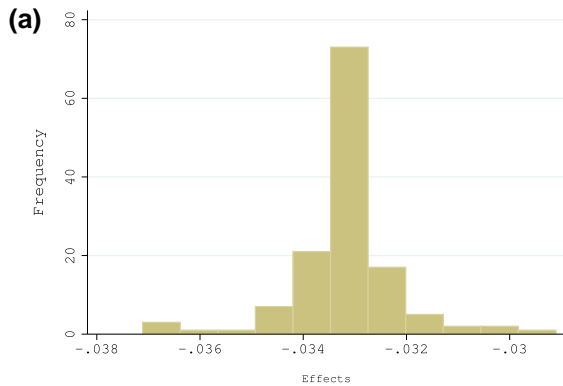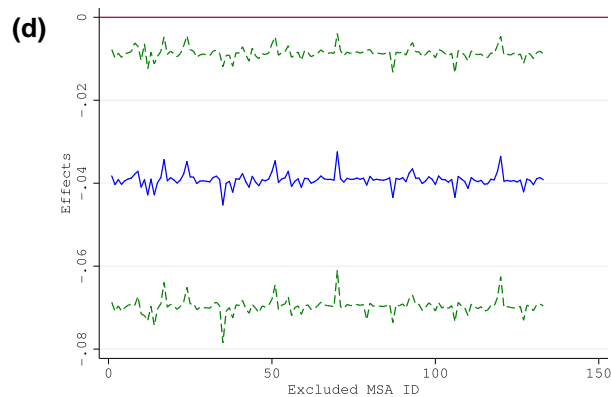
FIGURE 4 Robustness check (leave-one-out test). Subfigures on the left show the distribution of the estimates from the leave-one-out exercise. Subfigures on the right show the estimate of the effect when MSA ID in the corresponding *x*-axis is excluded from the regression. The blue line represents the 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. MSA, metropolitan statistical area

In the main empirical specification, we use aggregated rather than individual-level analysis. It is worth noting that since the robot exposure measure varies at the MSA level, only factors that vary at the MSA level are likely to be the source of omitted bias. Conducting the analysis at the individual level may have an advantage of an increase in the
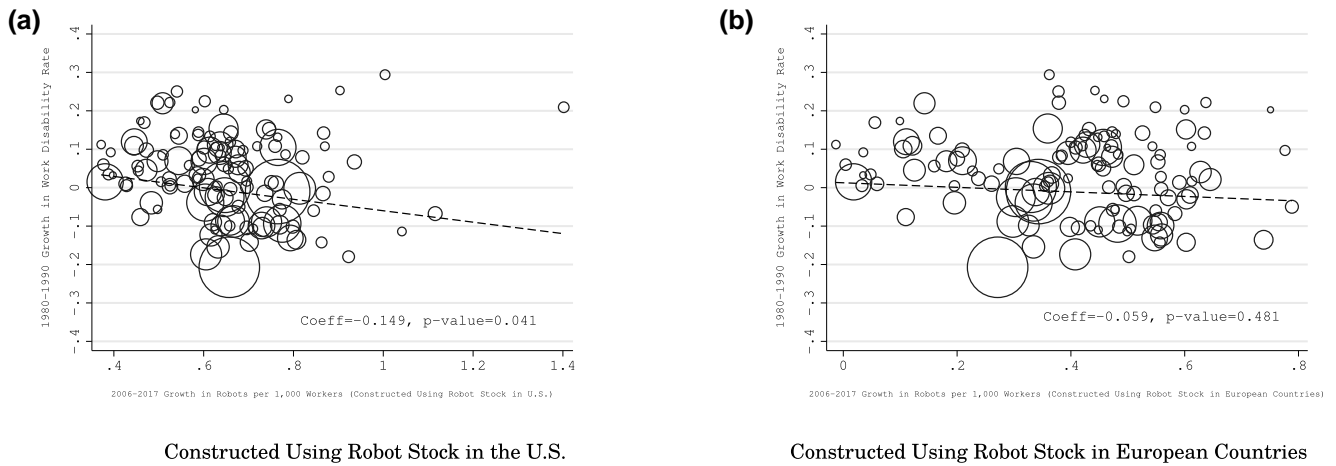
(a) Constructed Using Robot Stock in the U.S.

(b) Constructed Using Robot Stock in European Countries

FIGURE 5 Robustness check (pretrends analysis). Growth rates are calculated by taking first difference of natural log. The estimates for work disability rate among low-skilled workers with a high school diploma or less are calculated based on 1980 and 1990 IPUMS 5% Census data. Robot exposure measure is constructed based on IPUMS 5% 1960 Census and 2006-2017 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. MSA, metropolitan statistical area

precision of the estimates, since we can add individuals characteristics that help explain poor health outcomes. However, it comes at the cost of a sizable increase in computation time. Nevertheless, as a robustness check, we redo the main analysis at the individual level with added controls for individual characteristics such as age, race, and gender (Table A10). The main findings hold qualitatively.

As another robustness check, we estimate an alternative specification based on the long-run first difference model:

$$\Delta ln(y_m) = \alpha_1 \Delta ln(Robot_m) + \alpha_2 \Delta ln(X_m) + \Delta \varepsilon_m \qquad (4)$$

where $\Delta ln(y_m)$ is the change in the natural log of health outcomes in city m from 2006 to 2017, and $\Delta ln(robot_m)$ is the change in the natural log of robot exposure in city m from 2006 to 2017. Similar to before, X_m is a vector of city-level control variables which include the population share of Blacks, the population share of Hispanics, the population share of females, and the unemployment rate.

The results of this alternative specification are reported in Table A11. A 10% increase in robots per 1000 workers is associated with a 10% to 15% decline in the share of low-skilled population reporting poor health. The IV estimates are imprecise, but it still suggests that higher penetration of industrial robots in the local labor market by 10% is associated with a reduction in the share of low-skilled population reporting poor health by 5%–8%. The evidence also shows that robot exposure is negatively related to the share of low-skilled population reporting ever quit a job because of health reasons. Overall, the results from the long-run first difference model yield similar findings to the main specification.

3 | POTENTIAL MECHANISM

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 still unclear how the rise of robotic technology may affect health. We hypothesize that robots mainly substitutes for the physically demanding, and potentially dangerous, tasks which are usually done by low-skilled workers, nudging these workers towards occupations requiring less manual/hazardous 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 robot exposure, we use the information on the importance of physical abilities scores in a given occupation from the US Department of Labor O*NET dataset as a proxy for physical tasks supplied by the occupation.[20] O*NET ratings reflect experts' evaluation of how important an ability is in the occupation. Within the physical ability group, O*NET measures the importance of the following abilities

in a standardized scale ranging from 0 to 100: dynamic flexibility, dynamic strength, explosive strength, extent flexibility, gross body coordination, gross body equilibrium, stamina, static strength, and trunk strength.[21] 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.[22] We then calculate the average of the O*NET physical abilities rating for each occupation, normalizing it to be between 0 and 1 by dividing it by the maximum value observed in the data. After normalization, we assign each employed individual in CPS data the physical task score associated with their occupation. Finally, for each city × year cell, we calculate the weighted average of physical task score where the weights are the hours worked by the individual times his or her person weight. The weighted average value in a city × year cell then serves as a proxy for physically demanding tasks supplied in the city at a point in time, in which the higher value corresponds to more physically demanding tasks supplied by workers in the city. For ease of interpretation, we natural log-transformed this variable.

In Columns 1 and 2 of Table 4, we report the effect of robot exposure on the natural log of physically demanding tasks supplied by low-skilled workers. There is evidence that the rise of robotic technology is associated with a lower physically demanding task supplied by low-skilled workers: a 10% increase in robots per 1000 workers is associated with about a 0.7% decline in the task supplied. The IV model suggests that the magnitude of the effect is larger at −1.5%. The evidence also shows that this effect is mainly driven by men (Panels B and C), consistent with the finding in the previous section that the health effects of robots are concentrated among this group.

As an additional analysis, we examine whether the tasks associated with high fatality or injury supplied by low-skilled workers are affected by robot exposure. To do this, we first obtained the number of fatalities associated with each occupation from the 2000 Census of Fatal Occupational Injuries and crosswalked it at the two-digit level to IPUMS consistent occupation codes.[23] Then, we divide the number of fatalities by the number of workers employed in each occupation obtained from 2000 CPS ASEC to acquire the fatality rate corresponding to each occupation. Afterward, we follow a similar approach to the construction of physical tasks supplied by low-skilled workers from the O*NET data. That is, we normalize the fatality rate in each occupation to be between 0 and 1 by dividing it by the maximum fatality rate observed in the data, assign each individual in the CPS data the fatality rate score associated with their occupation, and take the weighted average where the weights are the hours worked by the individual times his or her person weight. The weighted average value in a city × year cell then serves as a proxy for high fatality task supplied in the city at a point in time, in which the higher value corresponds to more high fatality task supplied by workers in the city. We use a similar approach to construct the proxy for high injury tasks supplied by low-skilled workers in a city at a point in time. The injury rate associated with each industry is obtained from the 2000 Survey of Occupational Injuries and Illnesses, and we crosswalked it at the two-digit level to IPUMS consistent industry code (IND1990).[24] Similar to before, we natural log-transformed these variables for ease of interpretation.

The results of this exercise are reported in Columns 3–6 of Table 4. We fail to find evidence that robot exposure is associated with a statistically significant change in the high fatality task supplied by low-skilled workers. However, there is evidence that higher robot exposure lowers high injury tasks supplied by low-skilled workers. Focusing on the IV model, the estimates suggest that a 10% increase in robots per 1000 workers lowers the high injury task supplied by low-skilled workers by 1.5%, suggesting that these workers reallocate their labor from robot-intensive industries with high injury rate (e.g., manufacturing) to other less robot-intensive industries with low injury rate (e.g., services). Separating the analysis by gender, we find that this effect is mainly driven by men. A 10% increase in robots per 1000 workers is associated with an approximately 4% decline in high injury tasks supplied by male low-skilled workers, while the corresponding effects for women are much more muted.[25]

Overall, the evidence suggests that the effects of robots on the health of low-skilled workers can be partly explained by its effect on nudging workers toward tasks that are less physically demanding. Further analysis suggests that men are driving this result, consistent with the findings in the previous section that the health effects of robots are mainly concentrated among this group.

4 | 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

TABLE 4 The effect of robot exposure on the natural log of risky/physical tasks supplied by low-skilled workers

	Physical task		High fatality task		High injury task	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All						
OLS: ln (Robot exposure t-2)	−0.066*	−0.067*	0.033	0.036	−0.014	−0.012
	(0.038)	(0.039)	(0.104)	(0.104)	(0.032)	(0.032)
2SLS: ln (Robot exposure t-2)	−0.153**	−0.147*	0.041	0.061	−0.149**	−0.146**
	(0.074)	(0.075)	(0.210)	(0.215)	(0.058)	(0.059)
Observations	1739	1739	1739	1739	1739	1739
Panel B: Male						
OLS: ln (Robot exposure t-2)	−0.050	−0.052	0.148	0.140	−0.102	−0.070
	(0.034)	(0.033)	(0.093)	(0.092)	(0.069)	(0.070)
2SLS: ln (Robot exposure t-2)	−0.163**	−0.155*	0.231	0.234	−0.416***	−0.373***
	(0.081)	(0.080)	(0.209)	(0.213)	(0.126)	(0.124)
Observations	1739	1739	1739	1739	1739	1739
Panel C: Female						
OLS: ln (Robot exposure t-2)	0.008	−0.014	−0.025	−0.046	−0.016	−0.021
	(0.071)	(0.072)	(0.149)	(0.148)	(0.049)	(0.052)
2SLS: ln (Robot exposure t-2)	0.127	0.097	0.207	0.188	−0.044	−0.053
	(0.133)	(0.136)	(0.281)	(0.279)	(0.088)	(0.090)
Observations	1736	1736	1736	1736	1736	1736
Controls						
MSA and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA characteristics	No	Yes	No	Yes	No	Yes

Note: The estimates show the effect of robot exposure on the natural log of risky/physical tasks supplied by low-skilled workers. Low-skilled is defined as individuals with a high school diploma or less. Control for MSA characteristics include population share of female, population share of Blacks, population share of Hispanics, and unemployment rate. The instrument in 2SLS model is constructed based on the number of operational robots in European countries. The number of observations in Panel C is slightly lower because there are three city × year observations in which no low-skilled female workers are observed. All regressions are weighted by MSA population in 2000. Standard errors clustered at the MSA level are reported in parentheses.

Abbreviation: MSA, metropolitan statistical area.

*p < 0.1.

**p < 0.05.

***p < 0.01.

local economy will improve the health of low-skilled individuals in the locality by nudging these individuals toward occupations with lower intensity of physical tasks.

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 10% increase in robots per 1000 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 in response to robot exposure. A 10% increase in robots per 1000 workers is associated with a 1.5% decline in physical tasks and tasks with a high injury rate supplied by low-skilled workers.

The findings of this paper contribute to the policy discussion on the potential impacts of the rise of robotic technologies in the United States. So far, many studies have focused on the potential adverse labor market effects of robots. However, the adoption of robotic technologies is likely to have wider implications beyond the labor market. Some of these implications, undoubtedly, will have a positive effect on the overall welfare of the population. Indeed, the results

of the analysis suggest that higher penetration of industrial robots in the local labor market has the potential to improve the health of the population, especially those who are low-skilled, by nudging these individuals towards occupations with lower intensity of physical tasks.

CONFLICT OF INTERESTS
The authors declare that there are no conflict of interests.

DATA AVAILABILITY STATEMENT
The replication do-files that support the findings of this study are available from the corresponding author upon reasonable request. The Census and Current Population Survey data are publicly available and can be obtained from IPUMS (https://urldefense.com/v3/__https://ipums.org/__;!!N11eV2iwtfs!-Dp2PjyOtYPmq_rncR65D3rSPydDN-aLPBgdJTYjvuCrJaIE-PLV9RgSdHvWunrY$). The industrial robot data are not publicly available. However, it can be obtained from International Federation of Robotics (https://urldefense.com/v3/__https://ifr.org/__;!!N11eV2iwtfs!-Dp2PjyOtYPmq_rncR65D3rSPydDN-aLPBgdJTYjvuCrJaIE-PLV9RgSdBx_npV7$).

ORCID
Christian Gunadi https://orcid.org/0000-0002-3861-760X

ENDNOTES
[1] Supporting the argument that robots mainly substitutes for manual-intensive tasks, a recent study by de Vries et al. (2020) found that a rise in robot adoption is associated with a fall in the employment share of routine manual task-intensive jobs in high-income countries.

[2] As described later, we use the Department of Labor O*NET data and 2000 Survey of Occupational Injuries and Illnesses to calculate the physical tasks and tasks with high injury rate supplied by low-skilled workers.

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

[4] It is worth noting that Gihleb et al. (2020) documents evidence that an increase in robot exposure leads to an increase in mental health problems in the United States, presumably caused by the rise in economic uncertainty, consistent with studies that found deteriorating economic conditions are associated with worsening mental health in the population (Frasquilho et al., 2015; Modrek et al., 2015; Venkataramani et al., 2020). However, they do not find that this is the case in Germany. The authors attributed this difference to the lack of significant impact of robot penetration on labor market outcomes in Germany. In any case, Gihleb et al. (2020) findings on potential mental health effects suggest caution in the interpretation of our findings. That is, although we found that higher penetration of robots in the local labor market is positively related to the physical health of low-skilled individuals, their mental health could be adversely affected.

[5] Specifically, we use the Department of Labor O*NET data, Census of Fatal Occupational Injuries, and Survey of Occupational Injuries and Illnesses to assign each individual the physical/risky task score associated with their job. Then, we aggregated the data at the city and year level to examine the effect of robots on the risky/physical tasks supplied by workers. On the other hand, Gihleb et al. (2020) uses establishment-level data from Occupational Safety and Health Administration (OSHA) to analyze whether the rate of workplace injuries in an establishment is affected by the rise in industrial robots in the area where the establishment is located. It is unclear, however, if establishment-level analysis using OSHA data is necessarily better than our approach. As noted in Gihleb et al. (2020), there are a few limitations in using OSHA data. First, OSHA data is not representative of all businesses (i.e., OSHA only collects data from 1% of total establishments). In addition, not all states participate in the OSHA survey (there is no information for Alaska, Oregon, South Carolina, Washington, and Wyoming).

[6] 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 nonmanufacturing branches.

[7] To construct MSA-year aggregates, we use the CPS ASEC person-level weight (ASECWT).

[8] 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.

[9] The choice to use 2-year lagged effects may seem arbitrary. In the robustness check, we show that the findings are qualitatively similar when 1- or 3-year lagged robot exposures are used in the analysis.

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

[11] Indeed, robots are mainly used in manufacturing industries (Figure A2), many of whom employed low-skilled workers with a high school diploma or less (Watson, 2017).

[12] Evaluated at the sample mean, a 10% rise in robot exposure corresponds to approximately 0.05 standard deviation increase.

[13] It is worth noting that unlike Acemoglu and Restrepo (2020), we did not include Italy and Germany in the construction of the instrument. This is because of the weak first-stage relationship when we include Italy and Germany, with a robust first-stage F-statistics of 0.99. Since IV estimation with a weak first-stage is unlikely to yield reliable estimates, we do not include Italy and Germany in the construction of the instrument. The disagreement in the first-stage relationship between our work and Acemoglu and Restrepo (2020) could be due to the difference in the period of analysis. Nevertheless, when we include Italy and Germany in the construction of the instrument, the sign of IV estimates still show that robots are positively related to the health of low-skilled population.

[14] Following the discussion from Goldsmith-Pinkham et al. (2020) on the shift-share research design, since robots are mainly employed in the automotive industry (Table A2), our results will be mainly driven by this sector. The key assumption for the validity of the estimates, in this case, is that cities that have high growth of robot exposure (i.e., cities with a high share of the automotive industry in 1960) would have similar trends in health outcomes as cities that are experiencing low growth of robot per 1000 workers in the absence of the rise of robotic technology in the 1990s. We examine this assumption further in the robustness checks.

[15] In Table A4, we further separate the analysis by four education groups (high school dropouts, high school diploma, some college, college degree). As expected, the health effects of robotic technology are mainly concentrated among high school dropouts and individuals with only a high school diploma.

[16] Specifically, we focus on individuals who report living in the same house as 1 year ago.

[17] Following the suggestion by Goldsmith-Pinkham et al. (2020) to examine the correlates of industry shares in the base year, we report the local correlates of the share of the automotive industry, which is the most robotic-intensive industry, in Table A8. We find that the automotive industry in 1960 is negatively correlated with the population share of Hispanics, which is a cause for concern. However, similar to difference-in-differences methodology, the key assumption for the validity of the estimates is that cities with high growth of robot exposure (i.e., cities with a high share of the automotive industry in 1960) would have similar trends in health outcomes as cities that are experiencing low growth of robot per 1000 workers in the absence of the rise of robotic technology in the 1990s.

[18] Unfortunately, there is no information on poor health status and on whether an individual ever quit a job for health reasons in 1980 and 1990 IPUMS 5% Census, limiting the analysis only on the work disability rate.

[19] Although we checked for pretrends, it should be noted that the estimated effects of robots on health will be biased if there were unobserved shocks that occurred after 1990 that were specific to cities with high growth of robot exposure (i.e., cities with a high share of the automotive industry in 1960) and correlated with the outcomes. However, this concern is shared by virtually all studies that use shift-share methodology to evaluate the impacts of robot exposure in the United States.

[20] Similar to our work, many studies in the literature have used O*NET score as a proxy for the task associated with an occupation (e.g., Acemoglu & Autor, 2011; David & Dorn, 2013; Peri & Sparber, 2009).

[21] A higher score implies higher importance of the ability in the occupation. The description for each ability is reported in Table A12.

[22] Table A13 reports the 10 most/least physically demanding occupations based on O*NET ratings in the sample.

[23] The fatality rates across occupations are reported in Table A14. Occupations related to agriculture, production, and laborers often have the highest fatality rates.

[24] The injury rates across industries are reported in Table A15. Industries with the highest injury rates are concentrated in manufacturing, such as transportation equipment and lumber/wood products industries.

[25] In Tables 16 and A17, we also report the results when 1- or 3-year lagged robot exposures are used in the analysis. Although some of the estimates are imprecisely estimated, the findings qualitatively hold.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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