Industrial Robots and Workplace Fatalities and Hospitalizations*

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Abstract

This study measures the effect of industrial robots on workplace fatalities and hospitalizations at the commuting zone level in the US. The empirical strategy exploits potentially exogenous variation in robot exposure due to technological progress. Fatalities and hospitalizations are tabulated using inspection data from the Occupational Safety and Health Administration. The analysis indicates that industrial robots improved workplace safety, and this effect is most evident in automobile manufacturing. At the mean, industrial robots in automobile manufacturing account for approximately 28.7 percent of the decline in fatalities and hospitalizations overall.

Keywords: industrial robots, automation, workplace safety, occupational safety
JEL Codes: J81, I10

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1 Introduction

The adoption of industrial robots in the US workplace has increased steadily during the last three decades, as shown in Figure 1. To determine the welfare consquences of robotization, research must assess both its negative and positive consequences. A negative consequence of industrial robots, particularly for workers in the industries most affected, is a decrease in employment and wages (Acemoglu and Restrepo, 2020). A potential benefit, however, is improvements in workplace safety. Indeed, as Figure 1 illustrates, workplace fatalies and injuries decreased in tandem with the adoption of industrial robots, possibly reflecting a causal relationship. Industrial robots may improve safety by dissolving more dangerous employment and by improving working conditions among extant employment. The online retailer Amazon is an example, which aims to reduce recordable incidents by 50% through developing and testing robots for fulfillment centers.[1] Thus, to understand the effects of industrial robots on welfare, research must account for potential improvements in workplace safety.

To contribute to the research, this study estimates the effect of industrial robots on workplace fatalities and hospitalizations. Following Acemoglu and Restrepo (2020), the empirical strategy exploits variation in robot exposure across 722 commuting zones from 1993 to 2007. The measure of robot exposure combines variation in industry composition in a baseline year with industry-level changes in robot penetration over time, similar to a Bartik (1991) instrument. To tabulate fatalities and hospitalizations at the commuting zone level, we utilize inspection records from the Integrated Management Information System (IMIS) of the Occupational Safety and Health Administration (OSHA).[2] The OSHA accident rate is calculated as the number of fatalities or fatalities and hospitalizations, combined, per 100,000 workers. The denominator of the rate, employment by commuting zone, is tabulated from

[1] New technologies to improve Amazon employee safety (https://www.aboutamazon.com/news/innovation-at-amazon/new-technologies-to-improve-amazon-employee-safety).

[2] Lee and Taylor (2019) and Sojourner and Yang (2020) also measure workplace safety based on OSHA inspections due to severe and fatal accidents.

County Business Patterns (CBP). To support the use of IMIS data as a measure workplace safety, we benchmark the OSHA rates to the BLS fatality rate at the industry level and show that the two are highly correlated.[3]

The empirical analysis reveals several insights. First, the estimated effect of robot exposure on workplace fatalities is generally small and statistically insignificant. Second, the estimated effect of robot exposure on workplace fatalities and hospitalizations combined is negative and statistically significant, but implausibly large "at the mean" among all commuting zones. Third, the large magnitude is attributable to four outliers with respect to robot penetration: Detroit, Michigan; Lansing, Michigan; Saginaw, Michigan; and Cleveland, Ohio. These outliers reflect greater employment shares in automobile manufacturing, the industry with the greatest increase in robot penetration. The implausibly large estimates are not robust to the exclusion of the four outliers from the sample. Fourth, when the effect of robot penetration is allowed to differ between automobile manfucturing and all other industries, only the effect of industrial robots in automobile manufacturing is statistically significant. At the mean, industrial robots in automobile manufacturing account for approximately 28.7 percent of the decline in fatalities and hospitalizations overall.

A concern with the empirical strategy is the use of the Bartik-like instrument for identification. A recent critique of the Bartik instrument is that it depends on the exogeneity of "shares" across units of analysis (Adão et al., 2019; Goldsmith-Pinkham et al., 2020) - in this case industry shares across commuting zones. In effect, the identification strategy compares commuting zones with shares weighted towards industries with greater robot penetration to commuting zones with shares weighted towards industries with lesser penetration, and the concern is that the former may have exhibited improvements in workplace safety that were independent of industrial robots. One possibility is that demographic characteristics changed differentially across commuting zones that were both correlated with robot penetration and had a direct effect on workplace safety. Another possibility is that

[3] The BLS fatality data cannot be tabulated at the commuting zone level and thus is not suitable for analysis.

robot penetration may have been correlated with other capital improvements that improved workplace safety, such as automation that is not reprogrammable or multipurpose.[4] Because the empirical results are heavily driven by auto-centric Detroit, Michigan, this concern is especially problematic.

We provide three counterpoints. First, we control for changes in demographic characteristics over time, rather than just at baseline as in Acemoglu and Restrepo (2020). The results are robust to the inclusions of the additional control variables. Second, we provide a qualitative analysis of Detroit, highlighting how industrial robots may not only have improved workplace safety, but were specifically designed for tasks that were considered, "dirty, dull, and dangerous (Dolan, 2017)." Finally, we note that, while non-robotic automation is very likely correlated with industrial robot penetration, their effects on workplace safety are equally important to identify. In the absence of separate data on non-robotic automation, industrial robots serve as a proxy for automation more generally, and the effect estimates should be interpreted accordingly.

This study contributes to a growing literature on how industrial robots affect health. To our knowledge, only one study focuses on safety at the workplace, Gihleb et al. (2022). In their study, the outcome variable is the rate of cases involving days away from work, job restrictions, and job transfers. While the incidence of these cases is greater than the incidence of fatalities and hospitalizations, the value of statistical injury is substantially less than the value of life.[5] They find that a one standard deviation increase in their commuting zone-level measure of robot exposure decreased work-related annual injury rates by 1.2 cases per 100 workers. While their finding suggests that robots may decrease less severe cases involving days away from work, job restrictions, and job transfers, this effect may not necessarily extend to more severe cases of fatalities and hospitalizations.

[4] According to the International Federation of Robotics (IFR), an industrial robot is defi
ned as "automatically controlled, reprogrammable, and multipurpose."

[5] In 2020, the rate of total recordable injuries in private industry was 2.7 per 100 full-time equivalent workers, compared to the fatal work injury rate of 3.4 per 100,000 full-time equivalent workers. The value of a statistical life is orders of magnitude larger than the value of a statistical injury, estimated to range from $6.3 to $15.2 million and from $25,000 to $89,000, respectively.

Additional research examines the effects of industrial robots on health at the population level. First, using data from the Current Population Survey, Gunadi and Ryu (2021) conclude that industrial robots improved self-reported health among low-skilled workers, possibly reflecting a shift away from physical tasks. Second, using data from the Center for Disease Control and Prevention and the Behavioral Risk Factor Surveillance System, Gihleb et al. (2022) find that industrial robots increased drug and alcohol-related deaths, decreased job intensity and disability, but had no effects on mental health and work and life satisfaction. Finally, O'Brien et al. (2022) find that industrial robots increased all-cause mortality at the population level.

Collectively, the research suggests that industrial robots may have improved safety in the workplace, but only for less severe cases such as days away from work and hospitalizations, and not more severe cases of fatalities. However, the net effect of industrial robots on population health remains inconclusive.

2 Empirical Model

The empirical objective is to estimate the effect of robot exposure on workplace safety in the US. Following Acemoglu and Restrepo (2020), the empirical strategy exploits variation in robot exposure across 722 commuting zones. The model is given by the following equation:

$$\Delta Y_{ct} = \beta_0 + \beta_1 \Delta \mathrm{RE}_{ct} + \beta_2 X_{ct} + \tau_t + \varepsilon_{ct}. \tag{1}$$

ΔY_{ct} is the change in workplace safety in commuting zone c in period t, $\Delta \mathrm{RE}_{ct}$ is the change in robot exposure, and ε_{ct} is the error term. The model controls for commuting zone characteristics X_{ct} and period fixed effects τ_t.

To construct variation in robot exposure at the commuting zone level, we combine variation in industry composition across commuting zones with robot penetration by industry at the aggregate level, similar to the Bartik (1991) instrument. Specifically,

$$\Delta \mathrm{RE}_{ct} = \sum_i l_{cit} \Delta \mathrm{APR}_{it}. \tag{2}$$

The term l_{cit} is the share of employment in commuting zone c dedicated to industry i at period t, and $\Delta\mathrm{APR}_{it}$ is the aggregate change in robot penetration in industry i, adjusted for robot growth due to industry expansion. A general formula for the latter is given by the following equation:

$$\Delta \mathrm{APR}_{it} = \frac{M_{it'} - M_{it}}{L_{it}} - g_{it}\frac{M_{it}}{L_{it}} \tag{3}$$

The first term measures the increase in robots $M_{it'} - M_{it}$ relative to employment L_{it} in thousands of workers, and the second term g_{it} adjusts for changes in robots due to industry growth. The intuition is that, by measuring robot exposure based on aggregate trends, variation in exposure across commuting zones is attributable to systemic technological progress rather than factors specific to commuting zones.

A concern for identification is that industry composition, upon which robot exposure is based, may be correlated with other factors that affect workplace safety. If these other factors were omitted from the model in equation (1), their impact on workplace safety would be improperly attributed to robot exposure in the estimation of β_1. To address this issue, the model includes commuting zone characteristics X_{ct} and period fixed effects τ_t. The commuting zone characteristics are provided by Acemoglu and Restrepo (2021) and include the log of the population, share of females, share aged 65 and older, shares of educational attainment (no college, some college, college professional degree, and masters or doctoral degree), shares of race (Whites, Blacks, Hispanics, and Asians), share of employment in manufacturing, share of employment in light manufacturing, and share of female employment in manufacturing. These data come from the US Census. The model also includes measures of import competition from China (Autor et al., 2013) and the share of routine occupations (Autor and Dorn, 2013). Finally, the model controls the changes in demographic characteristics over the analysis period. This addresses the concern that changes in demographics may have a direct effect on workplace safety and are correlated with industry composition and thus robot penetration.

3 Data

3.1 Robots

Robot exposure is measured using survey data from the International Federation of Robotics (IFR).[6] Since 1993, the IFR has collected annual information on industrial robots for over 50 countries. For many European countries, the data were collected by year and industry since 1993. For the US, aggregate data have been collected since 1993, but data by industry are available only for 2004 onwards. When reported by industry, the IFR utilizes 19 broad classifications, 13 of which are in manufacturing.[7]

To estimate the effect of robot exposure on workplace safety using equation (1), we utilize IFR data provided by Acemoglu and Restrepo (2020) and follow their convention. First, we estimate a stacked difference model between 1993 and 2000 and 2000 and 2007. Second, to construct the adjusted measure of robot penetration in equation (3), we use robot data for five European countries: Denmark, Finland, France, Italy, and Sweden. Specifically, the adjusted robot penetration in equation (3) is calculated using the following equation:

$$\Delta \text{APR}_{it}^{Euro} = \sum_j \frac{1}{5} \left(\frac{M_{it'}^j - M_{it}^j}{L_{i,1990}^j} - g_{it}^j \frac{M_{it}^j}{L_{i,1990}^j} \right), \tag{4}$$

with employment L_{it} measured in 1990. As Acemoglu and Restrepo (2020) argue, using

[6] The IFR data come from Acemoglu and Restrepo (2021).

[7] The industries are agriculture, automotive, construction, electronics, food and beverage, wood and furniture, miscellaneous manufacturing, basic metals, industrial machinery, metal products, minerals, mining, paper and printing, plastics and chemicals, education and research, services, textiles, utilities, and shipbuilding and aerospace.

robot data from Europe, which leads the US in robot adoption, further ensures that the measure of robot penetration reflects systemic technological progress rather than factors specific to US commuting zones.

Acemoglu and Restrepo (2020) note important properties of the robot exposure measures. First, the measure of robot penetration by industry in equation (4) using European data is highly correlated with the same measure using US data. This suggests robot penetration in the US is driven largely by technological progress, as measured by robot penetration in Europe. Second, the European-based measure in equation (4) does not appear to mimic other industry-level trends, such as import competition and offshoring. Third, the geographic variation in robot penetration is substantial. This variation persists even after excluding the automotive industry, which experienced the largest increase in robot penetration. Finally, robot exposure was associated with the number of robot integrators at the commuting zone level.[8] This suggests that the measures of robot exposure indeed reflects economic activity involving robots.

3.2 OSHA Accidents

To measure workplace safety as an outcome variable to equation (1), we use data on OSHA inspections of work-related fatalities or hospitalizations. OSHA defines a fatality as an employee death resulting from a work-related incident or exposure, and defines a catastrophe as the hospitalization of three or more employees resulting from a work-related incident or exposure. According to OSHA standard 1960.29(b), "each accident which results in a fatality or the hospitalization of three or more employees shall be investigated to determine the causal factors involved." According to OSHA directive CPL 02-00-137, exceptions include fatalities by natural causes (e.g. heart attack), workplace violence, and motor vehicle accidents on public roads or highways.

The data on OSHA inspections come from the IMIS (OSHA, 2021). The data are

[8] The data on robot integrators come from Leigh and Kraft (2018)

reported at the accident level and the individual level. At the accident level, the IMIS reports the name and address of the inspected establishment and the findings of the investigation. At the individual level, the IMIS includes the Fatality and Catastrophe Investigation Summaries derived from OSHA Form 170. These summaries provide additional information about the accident, including whether a worker had been hospitalized or had died. The accident-level data are merged with individual-level data to determine the number of workers involved in a particular accident and the number of workers who had died, if any.

Figure 2 illustrates the number of OSHA-inspected fatalities and hospitalizations from 1993 to 2011.[9] During this period, the number of fatality investigations averaged 1,838 per year, and the number of hospitalization averaged 2,176 per year. Inspections decreased around 2008, coinciding with the Great Recession.

The outcome variable in equation (1) is defined as the change in the natural log of the annual OSHA accident rate:

$$\Delta Y_{ct} = ln(Y_{ct'}) - ln(Y_{ct}). \tag{5}$$

The annual OSHA accident rate Y_{ct} is calculated as the number of OSHA-inspected fatalities or hospitalizations per 100,000 workers:

$$Y_{ct} = \left[\frac{A_{ct} + 1}{E_{ct}}\right] 100,000. \tag{6}$$

The numerator A_{ct} is the number of OSHA-inspected fatalities and hospitalizations tabulated from the IMIS, and E_{ct} is employment and is tabulated from the Current Business Patterns.[10] Two rates are considered: fatalities only and fatalities and hospitalizations combined. To reduce noise, annual rates are calculated using three-, four-, and five-year averages. For

[9] Although catastrophe is defined as three or more hospitalizations, the Fatality and Catastrophe Investigation Summaries contain data on accidents with fewer than three hospitalizations and no fatalities. These accidents are included in the empirical analysis.

[10] To address the issue of taking the natural log of zero, the numerator is the number of OSHA-inspected fatalities or hospitalizations plus one.

example, to calculate the numerator in 1993 using a three-year average, the annual number of accidents is averaged across years 1993, 1994, and 1995. Inspections are assigned to commuting zones based on the zip code reported in the IMIS.

The Bureau of Labor Statistics also provides data on workplace safety, but these data are insufficient for estimating equation (1). The first data source comes from Survey of Occupational Injuries and Illnesses (SOII). These data report the total recordable case (TRC) rate per 100 full-time equivalent workers. The TRC rate includes illness and injuries involving days away from work, job restrictions, and job transfers. The second data source comes from the Census of Fatal Occupational Injuries (CFOI). These data report the fatality rate per 100,000 full-time equivalent workers. Neither the SOII nor the CFOI data are available at the commuting zone level and thus cannot be used for estimating equation (1).

Additionally, the OSHA rates that we derive from the IMIS are not directly comparable to the TRC rate or fatality rate computed by the BLS. In fact, during the analysis period, the total number of OSHA-investigated fatalities equals about 70% of the total number of fatalities reported in the CFOI. One reason is that OSHA does not have jurisdiction over all workplace fatalities, such as fatalities due to motor vehicle accidents that occur on public roads or highways.

Nonetheless, we compare OSHA and BLS data at levels for which data are available. Figure 2 plots the number of OSHA fatalities and hospitalizations alongside the number of BLS fatalities, which show similar trends over time. Figure 3 illustrates the relationship between the OSHA accident rates and the BLS rates by industry in 1993. Panel A is the OSHA fatality rate, and Panel B is the OSHA fatality and hospitalization rate. Each marker is an IFR industry, the size of the marker is proportional to employment in each industry, and both panels include the best linear fit.[11] As shown, the OSHA accident rates are positively correlated with the BLS fatality rate at the industry level. Weighted by employment, the correlation between the OSHA fatality rate and the BLS fatality rate is 0.816.

[11] The agricultural sector is excluded as the injuries and illnesses are likely to be underestimated (Leigh et al., 2014)

4 Results

4.1 Graphical Analysis

The relationship between robot penetration and workplace safety is first examined graphically. Figure 4 plots the outcome variable ΔY_{ct} in equation (1) against robot penetration $\Delta \mathrm{RE}_{ct}$ using three-year averages for the OSHA rate and stacked differences from 1993 to 2000 and from 2000 to 2007. Panel A is the OSHA fatality rate, and panel B is the OSHA fatality and hospitalization rate. Each marker is a commuting zone in one of the two time periods, the size of the marker is proportional to employment in each commuting zone, and both panels include the best linear fit weighted by commuting zone employment.

In Panel A, the relationship between between robot penetration and the OSHA fatality rate is only slightly negative. The greatest robot penetration occurred in the commuting zone of Detroit, Michigan, from 2000 to 2007, which lines up with the best linear fit. In contrast, the relationship between robot penetration and the OSHA fatality and hospitalization rate is more negative, as shown in Panel B. Additionally, the commuting zone of Detroit lies below the best linear fit. Taken together, an effect of robot penetration on workplace safety appears plausible for fatalities and hospitalizations, but less so for fatalities alone. Moreover, the effect on fatalities and hospitalizations appears attributable in large part to populous Detroit.

4.2 Regression Analysis

Table 1 presents the estimated effect of robot penetration on OSHA fatalities using equation (1). Panels A, B, and C differ by the number of years used to calculate the average OSHA fatality rate, and the columns correspond to models that differ by control variables. In column (1), where the model contains no control variables, the relationship between robot penetration and the OSHA fatality rate is negative. The negative relationship is not statistically significant using a three-year average, but is significant at the five percent level using a four-average and at the ten percent level using a five-year average.

In contrast, in column (2), where the model includes region and period fixed effects, the estimates become positive and statistically insignificant. The change in sign is attributable specifically to the inclusion of period fixed effects, rather than region effects. This reflects that the average growth in robot exposure was greater from 2000 to 2007 compared to 1993 to 2000 (1.40 and 0.65, respectively) and that the average decline in the fatality rate was greater from 2000 to 2007 compared to 1993 to 2000 (-0.13 and -0.03, respectively). Thus, the slightly negative relationship between robot penetration and the OSHA fatality rate in panel A of Figure 4 and column (1) of Table 1 is not robust to period effects.

The models in columns (3) through (6) introduce additional control variables, specifically demographic characteristics in levels (3), industry employment (4), Chinese import competition and share of routine employment (5), and changes in demographic characteristics (6). As shown, the control variables account for variation in workplace fatalities, increasing the R-squared from 0.03 in column (2) to 0.104 in column (6), but the relationship between robot penetration and the OSHA fatality rate remains positive and statistically insignificant.

Using the same specifications in Table 1, Table 2 presents the estimated effect of robot penetration on OSHA fatalities and hospitalizations. In contrast to fatalities, the estimated effect of robot penetration on fatalities and hospitalizations is negative across all specifications. Moreover, all but one of the estimates is statistically significant at the ten percent level, and several are significant at the one percent level. Thus, a causal effect of robot penetration on fatalities and hospitalizations seems more plausible.

One concern, however, is that the estimated effects on fatalities and hospitalizations at the mean are implausibly large. For example, the point estimate in panel A, column 6, is -0.129. In comparison, the weighted mean of robot exposure is 1.05, and the weighted mean of the outcome variable is -0.087. Taken together, the estimated effect of robot penetration at the mean, determined by multiplying -0.129 and 1.05, exceeds the average decline in hospitalizations of -0.087.

The implausibly large point estimates reflect that the least squares estimand is highly sensitive to outliers. As shown in Figure 4, an outlier with respect to robot penetration and fatalities and hospitalizations is Detroit from 2000 to 2007. The relatively large increase in robot penetration in Detroit reflects two factors. First, a substantial share of employment in Detroit is in automobile manufacturing in comparison to other commuting zones. Second, automobile manufacturing exhibited the greatest increase in robot penetration among the IFC industries. Three other commuting zones that have larger shares in automobile manufacturing also exhibited larger increases in robot penetration: Lansing, Michigan; Saginaw, Michigan; and Cleveland, Ohio. Interestingly, among these four commuting zones, hospitalizations decrease as robot adoption increases.

To assess the sensitivity of the estimates in Table 2 to the four outliers, Table 3 excludes the outliers from the sample.[12] As shown, many of the estimates are positive and statistically insignificant. The estimates that remain negative are smaller in absolute value in comparison to Table 2, and the only statistically significant estimate, in Panel C, column (1), is not robuts to the inclusion of control variables. The main conclusion from these results is that the effect of robot penetration on fatalities and hospitalizations is most likely to be found among the four outliers, and more specifically in Detroit.

Another approach to understanding the role of the automobile industry is to include separate measures for robot penetration in the automobile industry and robot penetration in all other industries. The results from the models are presented in Table 4. As shown, the estimated effect of robot penetration on fatalities and hospitalizations appears greater for industrial robots in automobile manufacturing compared to other industries, although the differences are not statistically significant. Regarding automobile manufacturing, all the estimates are negative and statistically significant at the five percent level, and many

[12]The four outliers are excluded in both periods, decreasing the sample size by eight.

are statistically significant at the one percent level. In comparison, the estimated effects of industrial robots in other industries are smaller in absolute value, and most are statistically insignificant.

When interpreting the results in Table 4, it is important to consider the estimated effects sizes in comparison to the change in robot penetration. Although automobile manufacturing represents just one of 19 IFR industries, it represents a significant share of the change in robot penetration. This is evident by the mean values of the robot penetration variables: the mean value for industrial robots in automobile manufacturing is 0.28, compared to 0.77 for all other industries. Factoring these means with the estimates in Panel A column (6), for example, yields -0.037 for automobile manufacturing and -0.077 for other industries. These figures, in comparison to the mean of the outcome variable of -0.129, imply that the aggregate decline in fatalities and hospitalizations is only partially attributable to automobile manufacturing, at the mean accounting for approximately 28.7 percent. The standard errors for industrial robots in other industries do not rule out potentially large and economically meaningful effects.

4.3 Qualitative Analysis of Automobile Manufacturing

According to the results, industrial robots are associated with improvements in workplace safety. The case is strongest for industrial robots in automobile manufacturing and with respect to fatalities and hospitalizations combined, rather than fatalities alone.

To understand the mechanism for these findings, we turn to qualitative anlaysis of automobile manufacturing. According to a study by the Brookings Institute, the automobile industry employed nearly half of all industrial robots (Muro, 2017). This accounts for the outliers in robot penetration such as Detroit and Lansing, Michigan, with Detroit alone adopting more than three times the number of industrial robots than any other metro area (Muro, 2017). Thus, auto-centric commuting zones are informative outliers with respect to robot penetration and workplace safety.

According to the director of manufacturing, engineering, strategies and standards at the International Automotive Components' (IAC) plant, located in Ohio, robot development is focused on tasks that are "dirty, dull, and dangerous (Dolan, 2017)." For example, robots that paint reduce workers' exposure to potentially toxic chemicals, and robots that perform tedious tasks reduce repetitive strain injury (Dolan, 2017). This may lead to the dissolution of more dangerous occupations or, at the very least, dangerous or repetitive tasks performed by humans. According to IAC officials, their workforce has been only minimally affected by industrial robots, and workers replaced by robots were temporary employees or permanent employees reassigned to other tasks (Dolan, 2017). Nonetheless, research by Acemoglu and Restrepo (2020) suggests that industrial robots decreased aggregate employment, and this effect is not unique to industrial robots in automobile manufacturing. Thus, the effect of industrial robots on fatalities and hospitalizations likely reflects a combination of dissolving dangerous occupations and making extant employment safer, with a potentially negative effect on employment overall.

5 Conclusion

During the past three decades, workplace accidents and fatalities decreased as the penetration of industrial robots increased. In this paper, we attempt to identify the causal effect of industrial robots on workplace safety at the commuting zone level. For identification, we exploit plausibly exogenous variation in robot exposure by combining variation in industry composition across commuting zones with robot penetration by industry. To measure workplace safety at the commuting zone level, we use data on OSHA inspections following a work-related fatality or hospitalization.

We find negative and statistically significant effects of robot exposure on OSHA fatalities and hospitalizations combined, but not fatalities alone. Additionally, the effects on fatalities and hospitalizations are due largely to commuting zones that are heavy in automobile manufacturing. In fact, when robot penetration is measured separately for automobile facturing and all other industries, only the former has a statsitically significant effect on workplace safety. According to qualitative analysis, the effect of robot penetration on workplace safety likely reflects both the dissolution of dangerous occupations and the improvement in safety among extant employment.

This study contributes to a growing literature on the effects of industrial robots in the workplace. This study is most comparable to a recent study by Gihleb et al. (2022). The authors examine the effect of industrial robots on workplace injuries involving days away from work, job restrictions, and job transfers, and find that that robot exposure decreased work-related injuries. Taken together, these studies indicate that industrial robots may have decreased less severe work-related injuries involving days away from work or hospitalizations, but these effects do not appear to extend to more severe cases involving fatalities. This distinction is important, since the value of statistical life is orders of magnitude larger than the value statistical injury, estimated to range from $6.3 to $15.2 million and from $25,000 to $89,000, respectively. These findings, combined with related research on employment and wages, are important for understanding the overall welfare effects of industrial robots in the workplace.

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Table 1: Model of OSHA Fatality Rate and Robot Exposure, Stacked Difference Model, Commuting Zone Level

	(1)	(2)	(3)	(4)	(5)	(6)
A. Three-year average						
Robots	-0.031	0.018	0.022	0.017	0.020	0.024
	(0.020)	(0.019)	(0.018)	(0.018)	(0.018)	(0.019)
R-Square	0.004	0.030	0.067	0.069	0.074	0.104
B. Four-year average						
Robots	-0.038**	0.009	0.008	0.001	0.006	0.011
	(0.017)	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)
R-Square	0.007	0.042	0.075	0.077	0.085	0.110
C. Five-year average						
Robots	-0.047*	0.018	0.014	0.006	0.010	0.016
	(0.023)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
R-Square	0.012	0.087	0.121	0.124	0.129	0.164
Control Variables						
Region and period FE		X	X	X	X	X
Demographics			X	X	X	X
Industry				X	X	X
Other shocks					X	X
Change in demographics						X
Observations	1,444	1,444	1,444	1,444	1,444	1,444

The outcome variable is the change in the natural log of the OSHA fatality rate, and the explanatory variable of interest is robot exposure. The unit of observation is stacked differences from 1993 to 2000 and from 2000 to 2007 by US commuting zone. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports, the share of routine jobs, and change in demographic characteristics. Observations are weighted by the baseline employment. Robust standard errors are in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent, respectively.

Table 2: Model of OSHA Fatality and Hopitalization Rate and Robot Exposure, Stacked Difference Model, Commuting Zone Level

	(1)	(2)	(3)	(4)	(5)	(6)
A. Three-year average						
Robots	-0.104**	-0.102*	-0.102	-0.132**	-0.129**	-0.129**
	(0.041)	(0.056)	(0.064)	(0.060)	(0.058)	(0.056)
R-Square	0.043	0.078	0.124	0.147	0.155	0.162
B. Four-year average						
Robots	-0.093***	-0.082*	-0.086	-0.114**	-0.110**	-0.109**
	(0.029)	(0.045)	(0.052)	(0.048)	(0.046)	(0.044)
R-Square	0.040	0.099	0.140	0.160	0.166	0.176
C. Five-year average						
Robots	-0.094***	-0.063*	-0.064	-0.089***	-0.086***	-0.084***
	(0.018)	(0.034)	(0.039)	(0.033)	(0.032)	(0.031)
R-Square	0.045	0.130	0.172	0.189	0.196	0.206
Control Variables						
Region and period FE		X	X	X	X	X
Demographics			X	X	X	X
Industry				X	X	X
Other shocks					X	X
Change in demographics						X
Observations	1,444	1,444	1,444	1,444	1,444	1,444

The outcome variable is the change in the natural log of the OSHA fatality and hospitalization rate, and the explanatory variable of interest is robot exposure. The unit of observation is stacked differences from 1993 to 2000 and from 2000 to 2007 by US commuting zone. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports, the share of routine jobs, and change in demographic characteristics. Observations are weighted by the baseline employment. Robust standard errors are in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent, respectively.

Table 3: Model of OSHA Fatality and Hopitalization Rate and Robot Exposure, Stacked Difference Model, Commuting Zone Level, Excluding Outliers

	(1)	(2)	(3)	(4)	(5)	(6)
A. Three-year average						
Robots	-0.034	0.028	0.050	0.012	0.007	0.006
	(0.041)	(0.055)	(0.057)	(0.067)	(0.065)	(0.063)
R-Square	0.002	0.043	0.095	0.105	0.112	0.119
B. Four-year average						
Robots	-0.049	0.021	0.037	0.001	-0.003	-0.004
	(0.034)	(0.042)	(0.043)	(0.048)	(0.046)	(0.045)
R-Square	0.005	0.068	0.113	0.122	0.128	0.137
C. Five-year average						
Robots	-0.076**	0.016	0.032	-0.005	-0.009	-0.006
	(0.033)	(0.041)	(0.040)	(0.046)	(0.044)	(0.043)
R-Square	0.013	0.105	0.150	0.160	0.166	0.176
Control Variables						
Region and period FE		X	X	X	X	X
Demographics			X	X	X	X
Industry				X	X	X
Other shocks					X	X
Change in demographics						X
Observations	1,436	1,436	1,436	1,436	1,436	1,436

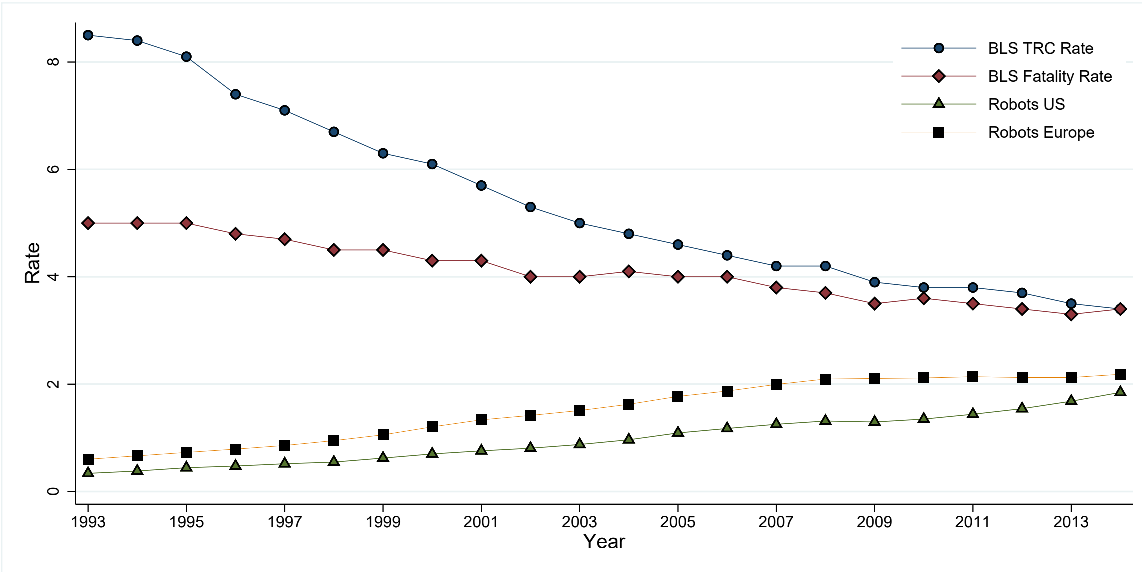
The outcome variable is the change in the natural log of the OSHA fatality and hospitalization rate, and the explanatory variable of interest is robot exposure. The unit of observation is stacked differences from 1993 to 2000 and from 2000 to 2007 by US commuting zone. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports, the share of routine jobs, and change in demographic characteristics. Observations are weighted by the baseline employment. Robust standard errors are in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent, respectively.

Table 4: Model of OSHA Hospitalization Rate and Robot Exposure, Stacked Difference Model, Commuting Zone Level

	(1)	(2)	(3)	(4)	(5)	(6)
A. Three-year average						
Robots, Auto	-0.114***	-0.115**	-0.118**	-0.139**	-0.133**	-0.133**
	(0.037)	(0.046)	(0.056)	(0.056)	(0.057)	(0.055)
Robots, Other	-0.068	-0.023	-0.008	-0.082	-0.105*	-0.100
	(0.046)	(0.067)	(0.064)	(0.066)	(0.061)	(0.061)
R-Square	0.044	0.081	0.128	0.148	0.155	0.163
B. Four-year average						
Robots, Auto	-0.098***	-0.096***	-0.103**	-0.122***	-0.116***	-0.115***
	(0.024)	(0.034)	(0.042)	(0.041)	(0.042)	(0.040)
Robots, Other	-0.076*	-0.001	0.017	-0.049	-0.067	-0.063
	(0.045)	(0.057)	(0.056)	(0.058)	(0.053)	(0.054)
R-Square	0.040	0.103	0.145	0.162	0.167	0.177
C. Five-year average						
Robots, Auto	-0.090***	-0.075***	-0.078**	-0.096***	-0.090***	-0.088***
	(0.018)	(0.026)	(0.031)	(0.029)	(0.030)	(0.028)
Robots, Other	-0.106**	0.005	0.020	-0.039	-0.059	-0.051
	(0.040)	(0.054)	(0.052)	(0.051)	(0.044)	(0.046)
R-Square	0.045	0.133	0.176	0.190	0.197	0.206
Control Variables						
Region and period FE		X	X	X	X	X
Demographics			X	X	X	X
Industry				X	X	X
Other shocks					X	X
Change in demographics						X
Observations	1,444	1,444	1,444	1,444	1,444	1,444

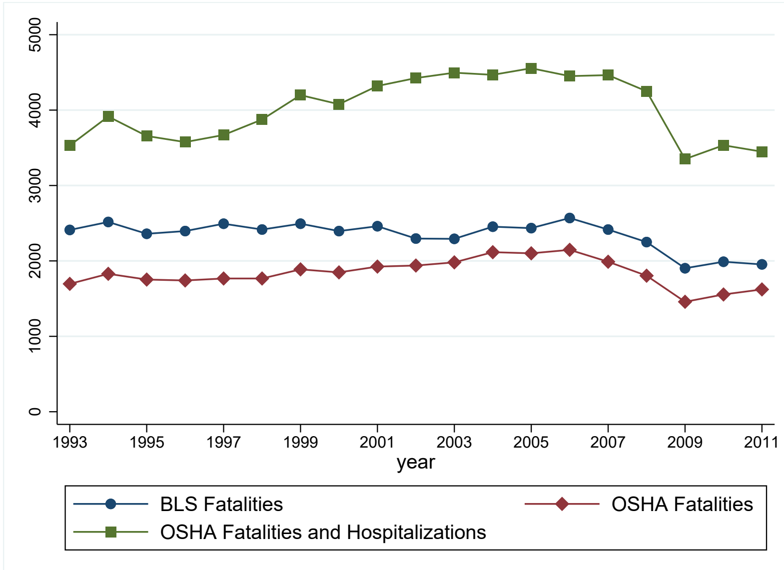
The outcome variable is the change in the natural log of the OSHA fatality and hospitalizationrate, and the explanatory variable of interest is robot exposure. The unit of observation is stacked differences from 1993 to 2000 and from 2000 to 2007 by US commuting zone. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports, the share of routine jobs, and change in demographic characteristics. Observations are weighted by the baseline employment. Robust standard errors are in parentheses. *, **, *** indicate statistical significance at the 10, 5, and 1 percent, respectively.

Figure 1: Trends in Workplace Safety and Robot Penetration



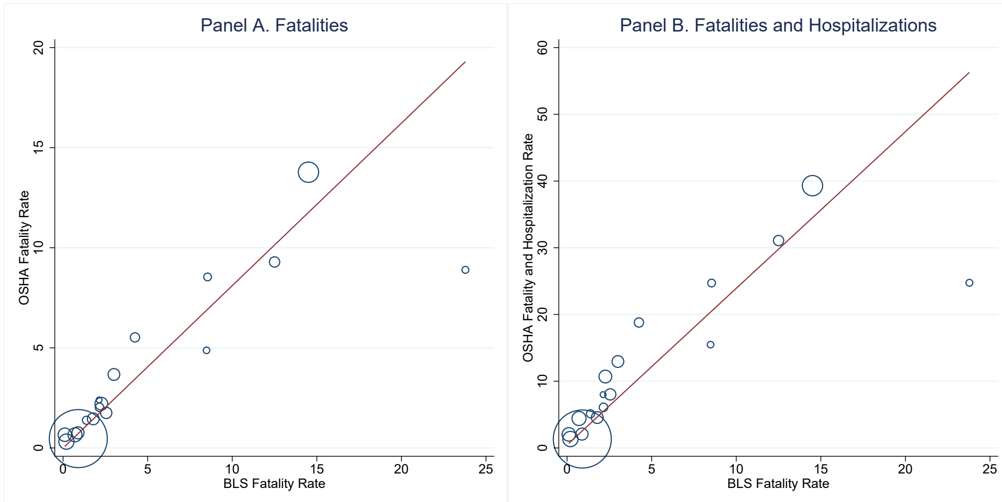
The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers, and the BLS fatality rate is the number of workplace fatalities per 100,000 full-time equivalent workers. Both figures come from the Bureau of Labor Statistics, Office of Safety, Health, and Working Conditions. Industrial robots are the number of robots per 1,000 workers in the US and in five European countries, including Denmark, Finland, France, Italy, and Sweden. The data on industrial robots come from the International Federation of Robotics.

Figure 2: Number of OSHA-Inspected Fatalities and Hospitalizations



The figure plots the annual number of BLS fatalities and the number of OSHA fatalities and hospitalizations. Due to the limited jurisdiction of OSHA inspections, BLS fatalities exclude transportation and violence. OSHA fatalities are tabulated from data on workplace inspections following fatal accidents.

Figure 3: Number of OSHA-Inspected Fatalities and Hospitalizations



The figure plots the relationship between the BLS fatality rate and OSHA rates by IFR industry. Panel A is the OSHA fatality rate, and panel B is the OSHA fatality and hospitalization rate. The marker size is proportional to employment, and the line is the best linear fit.

Figure 4: Number of OSHA-Inspected Fatalities and Hospitalizations