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The Effect of Industrial Robots on Workplace Safety

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Abstract

This study measures the effect of industrial robots on workplace safety at the commuting zone level, exploiting potentially exogenous variation in robot exposure due to technological progress. Workplace safety is measured by workers involved in severe or fatal accidents inspected by the Occupational Safety and Health Administration. From 2000 to 2007, we find that one additional robot in exposure per 1,000 workers decreased the OSHA accident rate at the mean by 15.1 percent. We also find that robot exposure decreased OSHA violations and accidents more likely to be affected by robot penetration, specifically those involving machinery or electrical.

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1 Introduction

Workplace safety in the US has improved substantially during the last three decades, but the mechanisms for this trend remain understudied. From 1993 to 2018, the rate of work-related injuries and illnesses decreased by 67.1 percent, from 8.5 per 100-full time equivalent workers to 2.8, and the rate of work-related fatalities decreased by 30 percent, from 5 per 100,000 full-time equivalent workers to 3.5 (Figure 1). Moreover, workplace safety improved within most industries, including construction and manufacturing, suggesting that the aggregate improvement in workplace safety does not simply reflect shifts in employment towards safer industries. In an article for the popular press, Krueger (2000) noted the improvements in workplace safety and discussed potential mechanisms.[1] In addition to rising incomes and costs of workers' compensation, he argued that capital investment likely decreased work-related injuries and illnesses, noting that the improvement in workplace safety in the early 1990s coincided with an investment boom when firms invested substantially in new - and potentially safer - facilities and equipment.

Motivated by this argument, we attempt to identify the effect of technological progress on workplace safety. We focus specifically on automation technology due to industrial robots using the empirical strategy of Acemoglu and Restrepo (2020).[2] According to data from the International Federation of Robotics (IFR), the use of industrial robots increased steadily in the US and Europe as early as 1993 (Figure 1), the first year in which data on robot penetration are available. Notably, the increased penetration of industrial robots in the US occurred in tandem with improvements in workplace safety. To examine causality, we examine the relationship between robot exposure and workplace safety at both the industry and commuting zone levels. At the commuting zone level, the measure of robot exposure combines variation in industry composition with industry-level changes in robot

[1] "Economic Scene; Fewer workplace injuries and illnesses are adding to economic strength." September 14, 2000. New York Times.

[2] An industrial robot is defined as automatically controlled, reprogrammable, and multipurpose (International Federation of Robotics, 2014)

penetration, similar to a Bartik (1991) instrument. To further isolate changes in robot exposure due to technological change, changes in robot penetration by industry are measured using data from Europe.[3]

The primary data on workplace safety come from the Integrated Management Information System (IMIS) (OSHA, 2021), a database of inspections conducted by the Occupational Safety and Health Administration (OSHA). We focus primarily on OSHA inspections due to severe exposures and accidents resulting in death or hospitalization of three or more employees, which we refer to as OSHA accidents. The OSHA accident rate is calculated as the number of workers involved in severe or fatal accidents per 100,000 workers, with employment figures derived from County Business Patterns (CBP).[4] The advantage of the OSHA accident rate - in comparison to rates of injuries and fatalities from the Bureau of Labor Statistics (BLS) - is that it can be calculated at the commuting zone level. Using industry level data, we show that the OSHA accident rate is highly correlated with the BLS fatality rate. Using the IMIS data, we also consider measures of OSHA enforcement from all inspections, not just those associated with severe or fatal accidents. The enforcement variables include the rate of inspections as well as violations and penalties as a result of inspections. If violations and penalties are indicative of workplace hazards and predictive of workplace accidents, then violations and penalties may also be viewed as measures of workplace safety.

We first examine correlations between robot penetration and workplace safety at the industry level, revealing several notable patterns. First, robot penetration from 1993 to 2007 was greater in more dangerous industries, measured by the BLS accident rate in 1993. There was no correlation, however, between robot penetration from 1993 to 2007 and the OSHA accident rate in 1993. Second, robot penetration from 1993 to 2007 was negatively correlated with the OSHA accident rate over the same period. This finding is consistent with

[3]The data for Europe come specifically from Denmark, Finland, France, Italy, and Sweden. For the US, robot data by industry are only available since 2004.

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

the conclusion that robot penetration improved workplaced safety. Third, robot penetration from 1993 to 2007 was not correlated with pre-existing trends in the OSHA accident rate, measured from 1986 to 1993. Thus, the negative correlation between robot penetration and the OSHA accident rate from 1993 to 2007 cannot be explained pre-existing trends.

We then estimate the effect of robot exposure on workplace safety at the commuting zone level. Following Acemoglu and Restrepo (2020), we estimate both a long difference model from 1993 to 2007 and a stacked differences model from 1993 to 2000 and from 2000 to 2007. We find no effect of robot exposure using the long difference, but find a negative effect using stacked differences. To understand the different results, we estimate the effect separately from 1993 to 2000 and from 2000 to 2007 and find that the negative effect occurred entirely in the latter period. The point estimate implies that a one robot increase in exposure per 1,000 workers decreased the OSHA accident rate at the mean by 15.1 percent. In comparison, the weighted average increase in robot exposure from 2000 to 2007 was 1.38 per 1,000 workers, and the OSHA accident rate in 2000 was 4.92 per 100,000 workers.[5]

We then estimate the effect of robot exposure on OSHA enforcement. We find negative and, in most cases, statistically significant effects of robot exposure on OSHA violations and penalties. To further assess whether the effect of robot exposure on violations can be attributed to robots, we estimate the effects separately by violation type, focusing on the ten most frequent types of violations in 1993. For each violation, we calculate an index of robot exposure based on the frequency of violations by type and industry and robot penetration by industry. We find that the negative effect of robot exposure on violations is most evident for those most exposed to robot penetration.

The results contribute to the literature on the labor market effects of robots.[6]

[5]The average is calculated across commuting zones from 2000 to 2007, weighted by employment.

[6]Recent contributions to the literature include Acemoglu et al. (2020); Dauth et al. (2021); Findeisen et al. (2021); Kugler et al. (2020); Dinlersoz and Wolf (2018). A closely related working paper by Gihleb et al. (2020) examines the effects of industrial robots on workplace safety in the US and Germany. Consistent with our results, they conclude that robot exposure decreased workplace accidents.

Graetz and Michaels (2018) attribute the rapid adoption of industrial robots in the US from 1990 to 2005 to an 80 percent decline in the cost of robots. By comparing county pairs from 1993 to 2005, they conclude that industrial robots increased annual labor productivity, but did not significantly affect employment. Acemoglu and Restrepo (2020) identify the effect of robot exposure on wages and employment using community-zone variation in robot exposure based on industry composition. They find robust negative effects of industrial robots on both wages and employment. Our findings suggest that robot penetration also improved workplace safety, either by displacing hazardous employment or by making employment safer. Improvements in workplace safety may also contribute to a decline wages, given that hazardous work conditions must be compensated with higher wages according to hedonic wage theory (Rosen, 1974).

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 by commuting zone. The model is given by the following equation:

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

ΔY_{ct} is the change in workplace safety in commuting zone c in period t, and $\Delta \text{Robots}_{ct}$ is the change in robot exposure. The model controls for commuting zone characteristics X_{ct} and period fixed effects τ_t. The standard errors ε_{ct} are robust and clustered at the commuting zone level.

To isolate potentially exogenous variation in robot exposure, we calculate the predicted change in robots for each commuting zone based on industry composition and robot penetration by industry. This is the empirical strategy of Acemoglu and Restrepo (2020) based on the Bartik (1991) instrument. Specifically, robot exposure for each commuting zone is calculated using the following equation:

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

The term l_{cit} is the share of employment in commuting zone c dedicated to industry i at period t, and ΔAPR_{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:

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

The first term measures the increase in robots relative to employment, and the second term adjusts for changes in robots due to industry growth g_{it}.

The identification assumption is that, by measuring robot exposure based on aggregate trends in robot penetration, the variation in exposure is due to systemic factors such as technological progress and thus exogenous to the structural error term at the commuting zone level in equation (1). If robot exposure were instead measured by actual robot penetration at the commuting zone level, the measure would likely be endogenous to workplace safety.

3 Data

3.1 Robots

Robot exposure is measured using survey data from the International Federation of Robotics (IFR).[7] Since 1993, the IFR has collected annual information on industrial robots

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

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.

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 long-difference model between 1993 and 2007 and 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 is calculated using the following equation:

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

In contrast to equation (3), the denominator is constructed using data in 1990. As Acemoglu and Restrepo (2020) argue, using robot data from Europe further ensures that the measure of robot penetration reflects technological progress and thus exogenous to workplace safety in equation (1).

An alternative approach is to measure predicted robot exposure using aggregate US data at the industry level, but instrument the US-based measure with the European-based measure in equation (4). Because US data by industry is available only for 2004 onwards, the earliest possible baseline year is 2004. The measure of robot penetration for the US is calculated using the following equation:

$$\Delta \mathrm{APR}_{i,2004}^{US} = \left(\frac{M_{it'} - M_{i,2004}}{L_{i,1990}} - g_{it} \frac{M_{i,2004}}{L_{i,1990}} \right). \tag{5}$$

Intuitively, the instrumental variable approach isolates variation in predicted US robot penetration based on aggregate US data in equation (5) that is attributable to the predicted US robot penetration based on aggregate European data in equation (4).

Acemoglu and Restrepo (2020) document important properties of the robot exposure measures, which we briefly discuss. First, the US-based measure in equation (5) is highly correlated with the European-based measure in equation (4). This suggests robot penetration in the US is driven largely by technological progress. 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 reflect robot-related activity.

3.2 OSHA Accidents

To measure workplace safety as an outcome variable to equation (1), we use data on OSHA inspections resulting from severe or fatal accidents. The data on OSHA inspections come from the IMIS (OSHA, 2021), which contains information on inspections as early as 1984. For each inspection record, the IMIS reports the name and address of the inspected establishment and the findings of the investigation. Importantly, if under OSHA jurisdiction, OSHA is required to investigate work-related accidents resulting in death or hospitalization of three or more employees.[9] In these cases, the IMIS also includes Fatality and Catastrophe Investigation Summaries from OSHA Form 170. Because the criteria for an inspection based on severe or fatal accidents are clear and relatively objective, we use these inspections to measure workplace safety, which we refer to as OSHA accidents.

The OSHA accident rate is calculated as the number of workers involved in an accident resulting in death or hospitalization of three or more employees per 100,000 workers by

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

[9]OSHA standard 1960.29(b) reads, "In any case, each accident which results in a fatality or the hospitalization of three or more employees shall be investigated to determine the causal factors involved."

commuting zone and period. In our analysis, we do not analyze fatalities and hospitalizations separately, as the data on fatalities are inconsistent.[10] To reduce noise, we calculate annual rates using a three-year average. For example, for the numerator in 1993, we calculate the annual average of accidents that occurred in 1993, 1994, and 1995. Inspections are assigned to commuting zones based on the zip code reported in the IMIS. For the denominator, we tally employment by commuting zone using CBP.

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 reflects 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. Both the SOII and CFOI data are available by year and industry, but not by commuting zone, and thus cannot be used for estimating equation (1).

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

To compare the correlation between the OSHA accident rate and the BLS rates, we calculate the OSHA accident rate by IFR industry using the SIC code reported in the IMIS. Figure 2 illustrates scatter plots of the OSHA accident rate and the BLS rates by

[10] The IMIS data include two variables on fatalities, one at the accident level and one at the individual level. However, when compared, the information on fatalities is highly inconsistent. For example, conditional on no fatality at the accident level, the individual level variable indicates that 14 percent of workers had died. We are therefore hesitant to draw definitive conclusions based on these variables and simply highlight the industry-level correlations between the OSHA accident rate and BLS fatality rates, illustrated in Figure 2.

industry in 1993, where the relative sizes of the scatter points are proportional to relative employment in each industry.[11] As shown, the OSHA accident rate is positively correlated with both BLS rates, but the correlation weighted by employment is greater for the fatality rate than the TRC rate: 0.92 versus 0.58. The high correlation between the OSHA accident rate and the BLS fatality rate, combined with the fact that workplace safety is measured as changes rather than levels in equation (1), provides assurance that the OSHA accident rate is a reasonable measure of workplace safety, with the important advantage that it can be calculated at the commuting zone level.

3.3 OSHA Enforcement

We also consider broader measures of OSHA enforcement using the IMIS. Specifically, we consider whether an establishment was inspected for any reason, not just due to severe or fatal accidents, as well as the violations and monetary penalties as a result of inspections. The violations and penalties are reported in separate files, which we merge to the inspection records.

For these measures, the rate is calculated per establishment by commuting zone, rather than by employment, as these outcomes occur at the establishment level. Again, we calculate annual rates using a three-year average. For the numerator, we calculate the annual average of any inspection, any violation, and any penalty. For violations and penalties, we also calculate the annual average of the number of violations and penalty amounts, with the latter converted to 2020 dollars using the Consumer Price Index. For the denominator, we tally establishments by commuting zone using CBP.

We note that OSHA enforcement outcomes are not direct measures of workplace safety. For example, the number of OSHA inspections may simply reflect administrative capacity rather than workplace safety. On the other hand, a negative association between

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

robot exposure and violations and penalties would be consistent with increased compliance with OSHA regulations or the displacement of more dangerous occupations.

3.4 Control Variables

The models include control variables provided by Acemoglu and Restrepo (2021): 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 models also include measures of import competition from China (Autor et al., 2013) and the share of routine occupations (Autor and Dorn, 2013).

4 Industry Correlations

We first examine industry-level correlations between robot penetration and workplace safety. One consideration is whether robot penetration was correlated with more dangerous industries. To explore this question, Figure 3 plots the relationship between robot penetration between 1993 and 2007 and workplace safety in 1993, where the relative sizes of the scatter points are proportional to the relative employment in each industry. Panel A corresponds to the TRC rate from the BLS, and panel B corresponds to the OSHA accident rate from the IMIS. As shown, the linear relationship in both figures is positive, indicating that more dangerous industries experienced greater robot penetration. To quantify these correlations, we regress changes in robot penetration on baseline workplace safety in 1993 weighted by employment in 1993. The coefficient on workplace safety is positive for both the TRC rate and OSHA accident rate, but only the former is statistically significant.

We next consider whether robot penetration was correlated with changes in workplace safety during the analysis period. To explore this question, Figure 4 plots the relationship between robot penetration and workplace safety using the stacked-model changes between 1993 and 2000 and 2000 and 2007. Again, panel A corresponds to the TRC rate from the BLS, and panel B corresponds to the OSHA accident rate from the IMIS. As shown, the linear relationship in both figures is negative, indicating that greater robot penetration was associated with a reduction in workplace accidents. To quantify these correlations, we regress changes in workplace safety on changes in robot penetration. The regression results are reported in Table 1. Panels A and B correspond to the long difference and stacked differences, respectively, and columns (1) and (2) correspond to the TRC rate and OSHA accident rate, respectively. In all specifications, industry-level observations are weighted by baseline employment. As shown, the negative relationship between robot penetration and workplace safety is negative and statistically significant. Moreoever, the results are robust to long difference versus stacked differences. These results indicate that robot penetration by industry was associated with improvements in workplace safety.

We next consider whether the negative correlations illustrated in Figure 4 may simply reflect trends in workplace safety before 1993. To explore this question, Figure 5 plots the relationship between robot penetration from 1993 to 2007 and changes in workplace safety from 1986 to 1993. In contrast to Figure 4, the relationship between robot penetration and workplace safety is not negative and, in fact, may be positive with respect to the TRC rate in panel A. It should be noted, however, that workplace accidents were generally increasing from 1986 to 1993 in Figure 5, but generally decreasing from 1993 to 2007 in Figure 4. To quantify the correlations in Figure 5, we regress changes in workplace safety from 1986 to 1993 on changes in robot penetration from 1993 to 2007 weighted by employment in 1993. The regression results are reported in Table 2. As shown, both estimates are small and statistically insignificant.

We also consider whether robot penetration was correlated with changes in OSHA enforcement at the industry level. To explore this question, Figure 6 plots the relationship between robot penetration and measures of OSHA enforcement using stacked differences between 1993 and 2000 and 2000 and 2007. As shown, there does not appear to be a systematic relationship between robot penetration and OSHA enforcement. The relationship with any inspection appears positive, whereas the relationship with violations and penalties appears zero or slightly negative. To quantify these correlations, we regress changes in OSHA enforcement on changes in robot penetration. The regression results are reported in Table 1. In addition to any violation and penalty as outcome variables, the table reports results for the number of violations and penalty amounts. As shown, most of the coefficients are small and statistically insignificant. One exception is any inspection, which appears to increase with robot penetration using stacked differences. The other exception is penalty amounts, which appears to decrease with robot penetration using both the long difference and stacked differences. Taken together, the results suggest that robot penetration was associated with an increase OSHA inspections, if at all, but was negatively associated with the amount of penalties levied on establishments as a result of an inspection. If OSHA penalties are indicative of workplace hazards and predictive of workplace accidents, the results suggest that robot penetration was associated with improvements in workplace safety.

5 Commuting Zone

5.1 Baseline Results

We next attempt to identify the causal effect of robot exposure on workplace safety by exploiting potentially exogenous variation in exposure at the commuting zone level. The baseline results come from estimating equation (1) using the European based measure of robot penetration given by equation (4). The results are presented in Table 3. Panels A and B correspond to the long difference and stacked differences, respectively. In all specifications, the outcome variable is expressed as changes in the natural log, and control variables are included.

Column (1) reports the results for the OSHA accident rate. As shown, the coefficient on robot penetration is negative using both long difference and stacked differences, but the coefficient is an order of magnitude larger using stacked differences. In that case, the coefficient implies that one additional robot in exposure per 1,000 employees decreased the OSHA accident rate at the mean by 15.7 percent. The estimated effect should be interpreted with caution, however, given that the estimate is not robust to the long difference specification and is statistically significant only at the ten percent level.

Columns (2) through (6) report the results for OSHA enforcement. In most cases, robot exposure appears to have decreased measures of OSHA enforcement, but for some measures the magnitudes and statistical significance differ between the long difference and stacked differences. In column (2), robot exposure appears to have decreased OSHA inspections, but the effect is larger and statistically significant using the long difference model. In columns (3) and (4), robot exposure appears to have decreased the rate of any violation as well as the number of violations. The estimates for any violation are similar using the long difference and stacked differences, but is statistically significant using stacked differences only. The estimates for the number of violations differ in sign, magnitude, and statistical significance between specifications, with the effect larger, negative, and statistically significant using stacked differences. In columns (5) and (6), robot penetration appears to have decreased the rate of any penalty as well as the penalty amount. The magnitude and statistical significance of the estimates for any penalty are robust to long versus stacked differences, whereas the estimate for the penalty amount is larger and statistically significant using stacked differences. Taken together, the results suggest that robot exposure decreased measures of OSHA enforcement, specifically inspections, violations, and penalties. As stated, if violations and penalties are indicative of workplace hazards and predictive of workplace accidents, the results suggest that robot exposure improved workplace safety.

5.2 Results by Period

In the preceding analysis, we follow the convention of Acemoglu and Restrepo (2020) by estimating long differences between 1993 and 2007 and stacked differences between 1993 and 2000 and between 2000 and 2007. However, for many outcomes we consider, the results differ in magnitude and statistical significance across specifications.

One possible explanation is that the variation in robot penetration between the two periods is driven by different industries and that the effect of robot penetration on workplace safety differs by industry. To examine this possibility, Figure 7 illustrates the correlation between robot penetration from 1993 to 2000 and from 2000 and 2007 by industry in Europe. As shown, early robot penetration is highly correlated with later robot penetration: the intra-industry correlation weighted by employment in 1993 is 0.94. This suggests that the variation in robot penetration was driven largely by the same indutries in both periods.

Another possible explanation is that robots adopted in the earlier period affected workplace safety differently than robots adopted in the later period, or that the effect of robot adoption on workplace safety is lagged with respect to the timing of adoption. To examine these possibilities, we estimate the models in Tables 1 and 3 separately by period. The results are presented in Tables 4 and Table 5, respectively. As shown, the negative effects for BLS TRC rate, the OSHA accident rate, and OSHA enforcement rates reported in the baseline results appear to be driven by robot penetration between 2000 and 2007. For that period, one additional robot in exposure decreased OSHA accidents at the mean by 15.1 percent, which is statistically signficant at the ten percent level. These results are consistent with both possible explanations: either robots adopted between 2000 and 2007 were more effective at reducing OSHA accidents and enforcement, or the safety effects of robot adoption between 1993 and 2000 do not manifest until 2000 and 2007. The latter explanation is possible because, as previously stated, robot penetration by industry is highly correlated between the two periods.

5.3 US-Based Measure of Robot Exposure

We next consider whether the baseline results are robust to using the US-based measure of robot penetration in equation (5), instrumented by the European-based measure in equation (4). We calculate the US-based measure using the available data during the analysis period, from 2004 to 2007, rescaled to reflect robot penetration over seven years, from 1993 to 2000 and 2000 to 2007.

The instrumental variable results using stacked differences, presented in Table 6, are consistent with the baseline results presented in Table 3. For example, the effect of robot exposure on the OSHA accident rate is -0.16 in Table 6 and -0.29 in Table 3. Both estimates are statistically significant at the ten percent level. The estimated effects on OSHA enforcement are also consistently negative in both tables, with the magnitudes slightly larger using instrumental variables. The robustness of the results reflect that the US-based measure is highly correlated with the European-based measure, as documented by Acemoglu and Restrepo (2020).

5.4 OSHA Violations by Type

The commuting zone results show that robot exposure decreased OSHA violations. To understand the mechanism for these results, we further examine whether the effect varied by violation type. This may have occurred for two reasons. First, violations differ by nature, and robots may have been more effective at reducing some types of violation than others. Second, robot penetration varied by industry, and some violations are more common in some industries than others. Using information on the nature of OSHA violations, we first categorized violations into broad categories using OSHA regulation standards and then estimated the effect of robot exposure on the ten most frequent violations.

The results are presented in Table 7. The first column lists the most frequent violations, and the second column presents the estimated effect of robot exposure for each violation. The empirical specifications are identical to column (2) of Table 3 using stacked differences. To convey the relative frequency of each violation, the third column reports the violation rate per 1,000 establishments. As shown, the four most frequent violations are toxic and hazardous substances, machinery and machine guarding, electrical, and general environmental controls. According to the regression results, the estimated effect of robot exposure is small and statistically insignificant for the most frequent violation, toxic and hazardous substances. For the other three violations, the estimated effect is negative and statistically significant, with the largest point estimate for the second most frequent violation, machinery and machine guarding.

The different results in Table 7 may simply reflect heterogeneous effects, independent of robot penetration by industry. However, if the different results reflect that robot penetration varied by industry, and that some violations occurred more frequently in some industries than others, then the effect sizes would be systematically correlated with robot penetration. To examine this possibility, the final column reports an index of robot penetration for each violation. To construct the index, we first tally the number of OSHA violations by IFR industry and violation type. For each violation type, we then calculate the share attributable to each industry. Finally, we use these shares as weights to calculate the average robot penetration from 1993 to 2007 for each violation. If all violations occurred in one industry, for example, then the robot index would equal the change in robots from 1993 and 2007 in that industry, regardless of that industry's size or the frequency of the violation.

Interestingly, among the top two most frequent violations, the effect of robot exposure on OSHA violations appears larger for violations with greater exposure to robot penetration. In first is hazardous substances, which had less robot exposure and where the effect of robot exposure was smaller and statistically insignificant. In second is machinery, which had more robot exposure and where the effect of robot exposure was larger and statistically significant. The next two violations - electrical and general environmental controls - fall between the first two violations with respect to both effect sizes and robot penetration. Beyond the top four, the relationship between effect sizes and robot penetration is not apparent, but these violations were also much less frequent. Taken together, the results suggest that the negative effects of robot exposure on OSHA violations was due in part to violations most exposed to robot penetration.

5.5 OSHA Accidents by Type

Given the results by type of OSHA violation in Table 7, we examine whether the decline in violations by type corresponds with a decline in accidents by type. To identify the latter, we search for keywords in the annotated descriptions of the accident included in the IMIS. Specifically, using data in 1993, we search for the keywords "toxic" and "hazardous" for "Toxic and Hazardous Substances," "machine" and "machinery" for "Machinery and Machine Guarding," and "electrical" for "Electrical." These keywords correspond to the top three violations listed in Table 7: toxic and hazardous substances, machinery and machine guarding, and electrical, respectively. We find that the accident rate with the keyword toxic to be rare: a rate of 0.080 per 100,000 workers, accounting for about 1 percent of all accidents. The accident rates with the keywords machinery and electrical are more common: rates of 0.430 and 0.265, respectively, accounting for 15 percent of all accidents. We therefore focus on the accident rates with the keywords machinery and electrical.

The results are presented in Table 8. The empirical specifications are identical to column (1) of Table 3 using stacked differences. In the first column, the point estimate for accidents involving machinery is -0.11. The estimate is smaller than the baseline estimate of -0.15 in Table 3, but is statistically significant at the five percent level. In the second column, the point estimate for accidents involving electrical is -0.18, which is statistically significant at the ten percent level. The third column reports the effect for accidents not involving mechanical or electrical, which comprise 85 percent of all accidents. In this case, the estimate is only -0.14 and not statistically significant. These results, combined with Table 7, indicate that greater robot exposure was associated with fewer violations and accidents involving mechanical and electrical, which were both more frequent and more exposed to robot penetration compared to other types of violations and accidents.

6 Magnitudes and Mechanisms

The empirical strategy identifies the effect of robot exposure on workplace safety by exploiting variation in exposure across US commuting zones. The results indicate that robot exposure improved workplace safety in affected commuting zones, and the effects were concentrated between 2000 and 2007. During that period, one additional robot in exposure per 1,000 workers decreased OSHA accidents at the mean by 15.1 percent, and the average increase in robot exposure weighted by employment was 1.38 per 1,000 workers. Thus, the average effect at the mean across commuting zones was 20.8 percent, compared to an average OSHA rate in 2000 of 4.92 per 100,000 workers. It should be noted, however, that point estimate is statistically significant only at the 10 percent level and thus does not rule out a wide range of effects. A smaller but more statistically significant effect was obtained for OSHA accidents involving machinery.

The effect of robot exposure reflects not only the direct effect of robots on workplace safety, but the spillover and agglomeration effects within commuting zones. In this context, a spillover effect would occur if improvements in workplace safety due to robot technology in one establishment forces other establishments, in equilibrium, to improve workplace safety, which may be accomplished with or without industrial robots. An agglomeration effect would arise if robot adoption by one establishment reduces the cost of robot adoption for nearby establishments. Agglomeration economies seem plausible given that robot integrators, an indicator of robot activity, are concentrated in only 19 percent of US commuting zones.[12]

The effect of robot exposure reflects safety improvements within employment, the displacement of more dangerous employment, or both. On one hand, Graetz and Michaels

[12]This number is calculated using data from Leigh and Kraft (2018) and provided by Acemoglu and Restrepo (2020).

(2018) find no effect of industrial robots on employment. In this case, the improvements in workplace safety reflect a decrease in workplace hazards in the same occupations or a shift in employment towards occupations or tasks that pose fewer workplace hazards. On the other hand, Acemoglu and Restrepo (2020) find negative effects of industiral robots on employment. In this case, the improvements in workplace safety may also reflect the displacement of dangerous jobs. This seems plausible, as the negative employment effects of Acemoglu and Restrepo (2020) are most evident in manufacturing and blue-collar, routine manual occupations.

The average effect at the mean is large compared to aggregate trends in workplace safety during the same period. For example, from 2000 to 2007, the OSHA rate itself declined by only 6.91 percent, from 4.92 to 4.58 per 100,000 workers.[13] A possible explanation is that, at the commuting zone level, the effect of robot exposure on workplace safety increases exponentially with exposure, perhaps due to spillover or agglomeration effects. To examine this possibility, we estimate the stacked differences model in Table 3 with robot exposure squared and find that only the coefficient on the squared term is both negative and statistically significant.[14] This suggests that the negative effect of robot exposure on workplace safety is driven by commuting zones with relatively high levels of exposure.

7 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, following Acemoglu and Restrepo (2020), we exploit plausibly exogenous variation in robot

[13]In comparison, the BLS TRC rate declined by 31.1 percent, from 6.1 to 4.2 per 1,000 full-time equivalent workers; and the BLS fatality rate declined by 11.6 percent, from 4.3 to 3.8 per 100,000 full-time equivalent workers.

[14]The point estimate for robot exposure is 0.151 (0.106), and the point estimate for robot exposure squared is -0.041 (0.011).

exposure based on the industry composition and robot penetration by industry. We find negative and statistically significant effects of robot exposure on OSHA accidents, violations, and penalties. These effects are concentrated between 2000 and 2007, rather than 1993 to 2000, which may reflect heterogenous effects across time or lagged effects from the early period to the later period. In the later period, one additional robot in exposure decreased the OSHA accident rate at the mean by 15.1 percent. We also find that the effect of robots is more evident for more frequent accidents and violations that were more exposed to robot penetration, specifically those involving machinery and electrical. The estimated effects reflect not only the direct effect of robot exposure on workplace safety, but also spillover and agglomeration effects within commuting zones.

While this study focuses on robot exposure due to techonological progress, one question that arises is the firm-level decision to adopt industrial robots. In a model of the firm, the optimal level of robots occurs where marginal revenue product of robots equals the marginal cost, accounting for technological substitutabilities between industrial robots, standard capital, and labor. Subsumed in this model are interesting factors related to workplace safety, including risk-aversion of labor, compensating wage differentials, and workers compensation policy. For example, more punititive workers compensation policy to protect workers may also hasten the displacement of employment, particularly when labor is highly risk averse. These questions are important directions for future research, especially as robot technology becomes more applicable to other industries and more ubiquitous in the workplace.

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Table 1: THE EFFECT OF ROBOT EXPOSURE ON WORKPLACE SAFETY, INDUSTRY LEVEL

	BLS TRC	OSHA Accident	Inspections	Violations		Penalties	
			Number	Any	Number	Any	Dollars
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Long Difference							
Robots	-0.017***	-0.013***	-0.003	-0.003	-0.006	-0.006	-0.021***
	(0.004)	(0.002)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)
Observations	18	18	18	18	18	18	18
B. Stacked Difference							
Robots	-0.018***	-0.014**	0.014**	0.020	-0.002	0.016	-0.022***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)	(0.012)	(0.005)
Observations	36	36	36	36	36	36	36

The unit of observation is industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The OSHA enforcement variables - inspections, violations, and penalties - reflect all inspections, not just accidents, expressed per 1,000 establishments. The outcome variables are calculated as the change in natural log, and robot exposure is calculated as the change in level. Panel A shows the long-difference estimates from 1993 to 2007, and panel B shows the stacked-difference estimates from 1993 to 2000 and from 2000 to 2007. Observations are weighted by the baseline employment. Robust standard errors are in parentheses.

Table 2: The Effect of Robot Exposure on Pre-Existing Trend in Workplace Safety, Industry Level

	BLS TRC	OSHA Accident
	(1)	(2)
Robot Exposure	0.007	-0.0002
	(0.007)	(0.004)
Observations	18	18

The unit of observation is industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The outcome variables are calculated as the change in natural log, and robot exposure is calculated as the change in level. The outcome variable is measured from 1986 to 1993, and the robot exposure variable is measured from 1993 to 2007. Observations are weighted by the baseline employment. Robust standard errors are in parentheses.

Table 3: THE EFFECT OF ROBOT EXPOSURE ON WORKPLACE SAFETY, COMMUTING ZONE LEVEL

	OSHA Accident	Inspections Number	Violations Any	Violations Number	Penalty Any	Penalty Dollars
	(1)	(2)	(3)	(4)	(5)	(6)
A: Long Difference						
Robots	-0.017	-0.050*	-0.040	0.004	-0.067***	0.022
	(0.027)	(0.029)	(0.027)	(0.028)	(0.023)	(0.029)
Observations	722	722	722	722	722	722
B: Stacked Difference						
Robots	-0.157*	-0.003	-0.037*	-0.071**	-0.053***	-0.111***
	(0.088)	(0.019)	(0.019)	(0.025)	(0.019)	(0.041)
Observations	1,444	1,444	1,444	1,444	1,444	1,444

The unit of observation is US commuting zones. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The OSHA enforcement variables - inspections, violations, and penalties - reflect all inspections, not just accidents, expressed per 1,000 establishments. The outcome variables are calculated as the change in natural log, and robot exposure is calculated as the change in level. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports and the share of routine jobs. Panel A shows the long-difference estimates from 1993 to 2007, and panel B shows the stacked-difference estimates from 1993 to 2000 and from 2000 to 2007. Observations are weighted by the baseline employment. Robust standard errors are in parentheses.

Table 4: The Effect of Robot Exposure on Workplace Safety by Period, Industry Level

	BLS TRC (1)	OSHA Accident (2)	Inspections Number (3)	Violations Any (4)	Violations Number (5)	Penalties Any (6)	Penalties Number (7)
Robots, 1993 to 2000	-0.004	0.0006	0.009	0.008	0.008	-0.007	-0.028***
	(0.003)	(0.008)	(0.014)	(0.013)	(0.012)	(0.008)	(0.006)
Robots, 2000 to 2007	-0.025***	-0.021***	0.017*	0.026**	-0.006	0.028*	-0.019***
	(0.008)	(0.005)	(0.008)	(0.011)	(0.003)	(0.015)	(0.004)
Observations	36	36	36	36	36	36	36

The unit of observation is industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The OSHA enforcement variables - inspections, violations, and penalties - reflect all inspections, not just accidents, expressed per 1,000 establishments. The outcome variables are calculated as the change in natural log, and robot exposure is calculated as the change in level. Observations are weighted by the baseline employment. Robust standard errors are in parentheses.

Table 5: The Effect of Robot Exposure on Workplace Safety by Period, Commuting Zone Level

	OSHA	Inspections	Violations		Penalty	
	Accident	Number	Any	Number	Any	Dollars
	(1)	(2)	(3)	(4)	(5)	(6)
Robots, 1993 to 2000	0.029	0.064	0.109	0.191*	0.031	0.001
	(0.142)	(0.097)	(0.090)	(0.099)	(0.095)	(0.133)
Robots, 2000 to 2007	-0.151*	-0.002	-0.037*	-0.071***	-0.053***	-0.108***
	(0.078)	(0.019)	(0.020)	(0.024)	(0.020)	(0.036)
Observations	1444	1444	1444	1444	1444	1444

The unit of observation is US commuting zones. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The OSHA enforcement variables - inspections, violations, and penalties - reflect all inspections, not just accidents, expressed per 1,000 establishments. The outcome variables are calculated as the change in natural log, and robot exposure is calculated as the change in level. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports and the share of routine jobs. Observations are weighted by the baseline employment. Robust standard errors are in parentheses.

Table 6: The Effect of Robot Exposure on Workplace Safety, Commuting Zone Level, US-Based Measure of Robots with Instrumental Variables

	OSHA Accident	Inspections	Violations		Penalty	
		Number	Any	Number	Any	Dollars
	(1)	(2)	(3)	(4)	(5)	(6)
US Robots	-0.287*	-0.005	-0.071	-0.136	-0.101	-0.206
	(0.154)	(0.035)	(0.033)	(0.045)	(0.033)	(0.072)
Observations	1,444	1,444	1,444	1,444	1,444	1,444

The unit of observation is US commuting zones. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The OSHA enforcement variables - inspections, violations, and penalties - reflect all inspections, not just accidents, expressed per 1,000 establishments. The US-based measure of robot penetration is calculated using data from 2004 to 2007, rescaled to seven years. The US-based measure is instrumented with the European-based measure from 1993 to 2007. The outcome variables are calculated as the change in natural log, and robot exposure is calculated as the change in level. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports and the share of routine jobs. The results come from the stacked-difference model from 1993 to 2000 and from 2000 to 2007. Observations are weighted by the baseline employment. Robust standard errors are in parentheses.

Table 7: THE EFFECT OF ROBOT EXPOSURE ON OSHA VIOLATION TYPE, COMMUTING ZONE LEVEL

Violation Type	Robots Estimate	Violation Rate	Robot Exposure Index
Toxic and Hazardous Substances	-0.023	6.93	5.29
	(0.046)		
Machinery and Machine Guarding	-0.236***	5.37	7.00
	(0.041)		
Electrical	-0.150**	4.90	6.35
	(0.074)		
General Environmental Controls	-0.123**	3.27	6.98
	(0.050)		
Hazardous Materials	0.020	2.36	7.94
	(0.042)		
Personal Protective Equipment	-0.153	2.15	6.62
	(0.111)		
Walking-Working Surfaces	-0.130***	1.74	6.70
	(0.040)		
Exit Routes and Emergency Planning	-0.042	1.36	6.14
	(0.053)		
Fire Protection	-0.169*	1.16	6.51
	(0.090)		
Materials Handling and Storage	0.013	1.12	8.54
	(0.036)		
Observations	1,444		

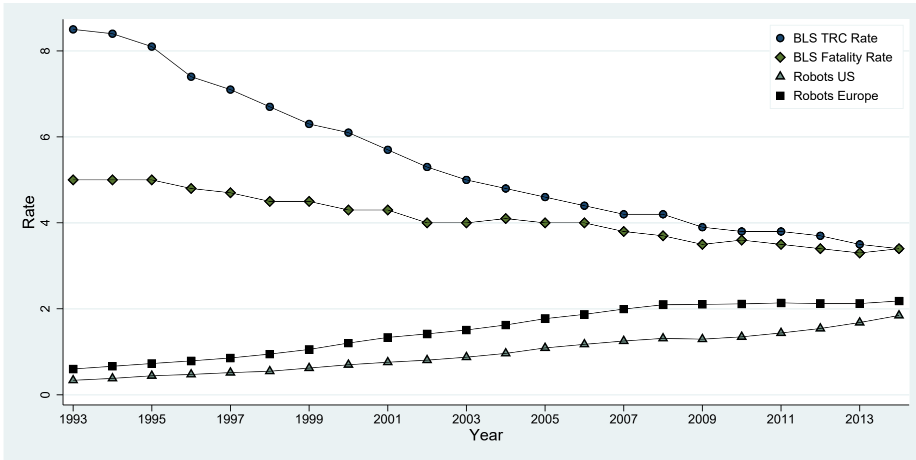
The unit of observation is US commuting zones. Each estimate comes from a single regression. The OSHA violation rate is calculated as the number of violations by type per 1,000 establishments. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports and the share of routine jobs. All estimates come from the long-difference estimates from 1993 to 2007. Observations are weighted by the baseline employment. Robust standard errors are in parentheses. The OSHA violation rate reported in the third column is calculated in 1993. The robot exposure index reflects the extent to which each violation type was exposed to robots based on violation rates in 1993 and robot exposure from 1993 to 2007.

Table 8: The Effect of Robot Exposure on OSHA Accident Type, Commuting Zone Level

	Machinery (1)	Electrical (2)	Other (3)
Robots	-0.105**	-0.180*	-0.140
	(0.046)	(0.099)	(0.086)
OSHA Accident Rate	0.430	0.265	4.583
Observations	1444	1444	1444

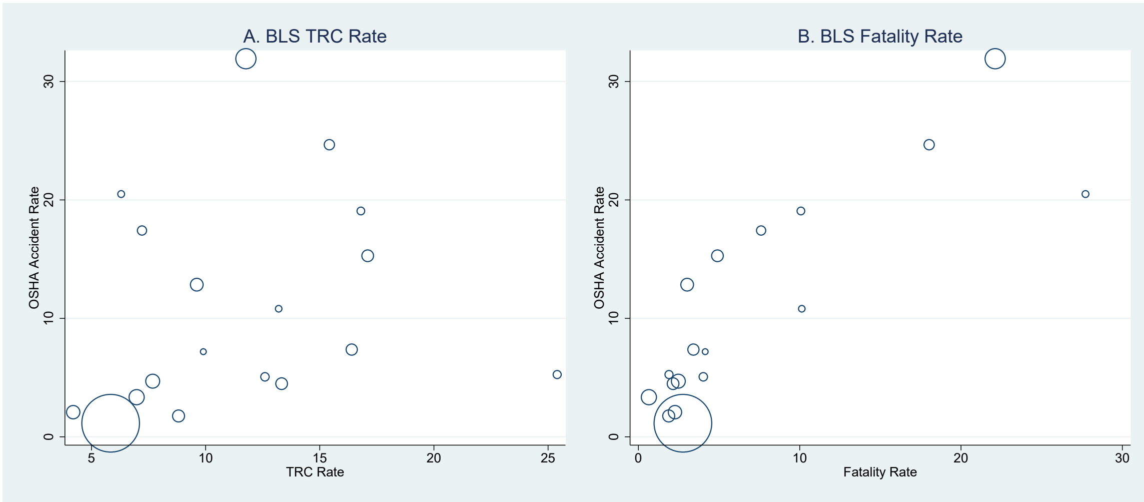
The unit of observation is US commuting zones. Each estimate comes from a single regression. The OSHA accident rate is calculated as the number of accidents by type per 1,000 establishments. The covariates include time period dummies, census division dummies, demographic characteristics, manufacturing share, exposure to Chinese imports and the share of routine jobs. All estimates come from the long-difference estimates from 1993 to 2007. Observations are weighted by the baseline employment. Robust standard errors are in parentheses. The OSHA accident rate is calculated in 1993.

Figure 1: Trends in Workplace Safety and Robot Penetration



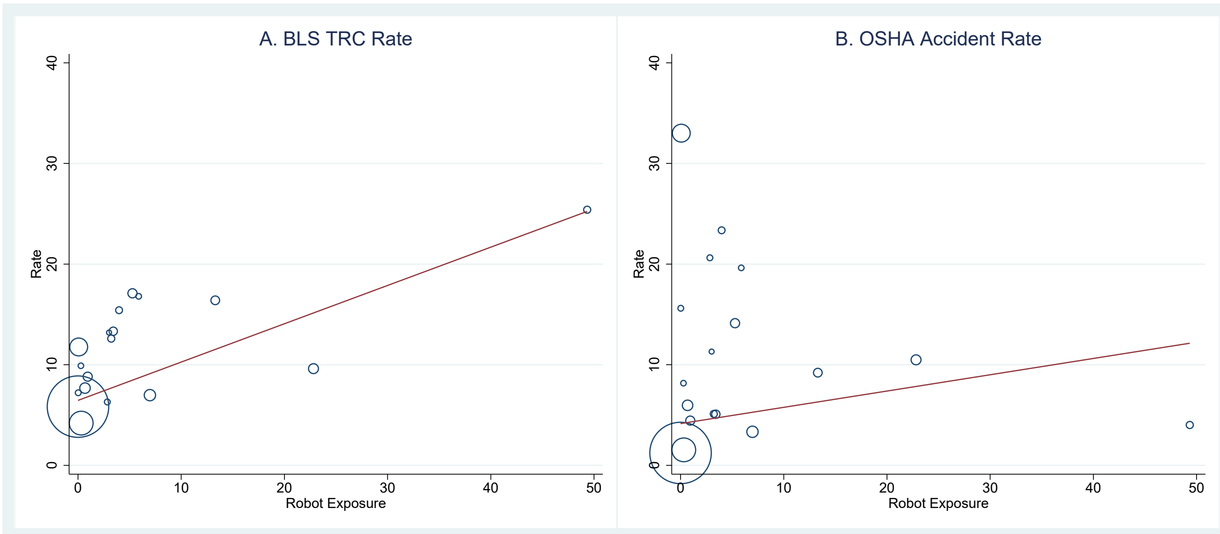
The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers, and the BLS fatality rate is the number of workplace fatalities per 100,000 full-time equivalent workers. Both figures come from the Bureau of Labor Statistics, Office of Safety, 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: OSHA Accident Rate vs. BLS Rates by Industry, 1993



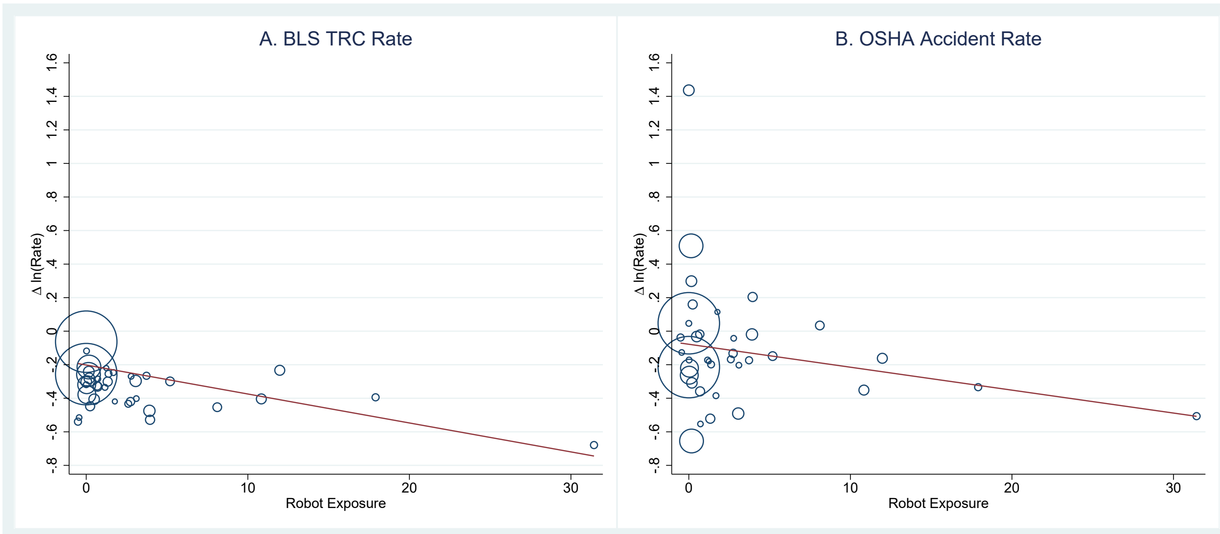
Each marker corresponds to an industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The BLS fatality rate is the number of workplace fatalities per 100,000 full-time equivalent workers. The marker size is proportional to employment data from the County Business Patterns. The weighted correlations in Panels A and B are 0.58 and 0.92, respectively.

Figure 3: Workplace Safety and Robot Exposure by Industry, Safety Baseline 1993 relative to Exposure 1993 to 2007



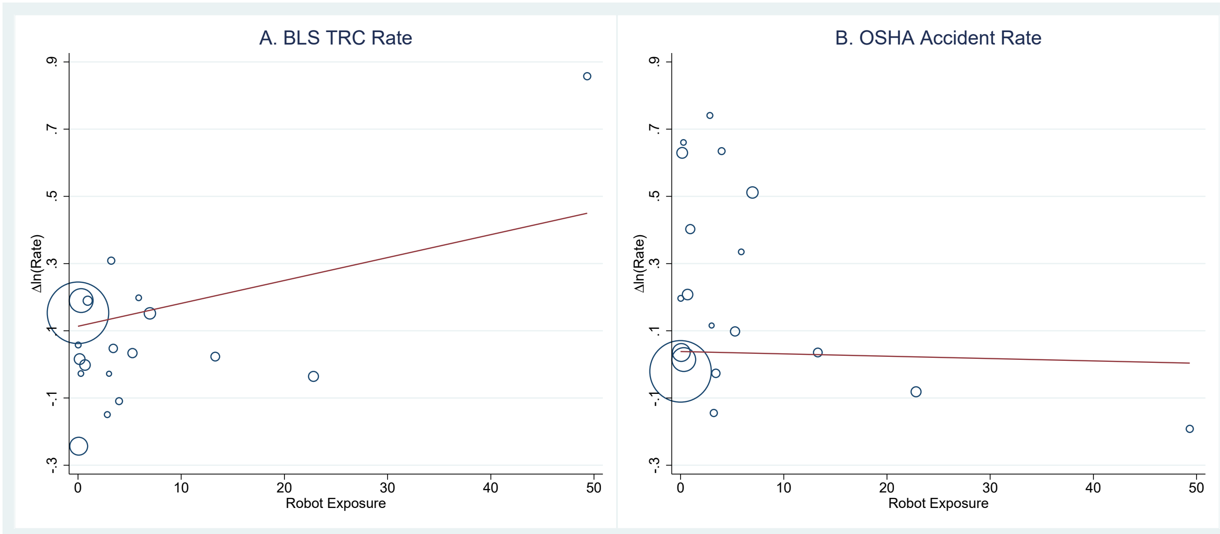
Each marker corresponds to an industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The marker size is proportional to employment data from the County Business Patterns. Workplace safety is measured in 1993. The exposure to robots is the change in number of robots per 1,000 workers by industry from 1993 to 2007 in five European countries, including Denmark, Finland, France, Italy, and Sweden.

Figure 4: Workplace Safety and Robot Exposure by Industry, Stacked Differences 1993 to 2000 and 2000 to 2007



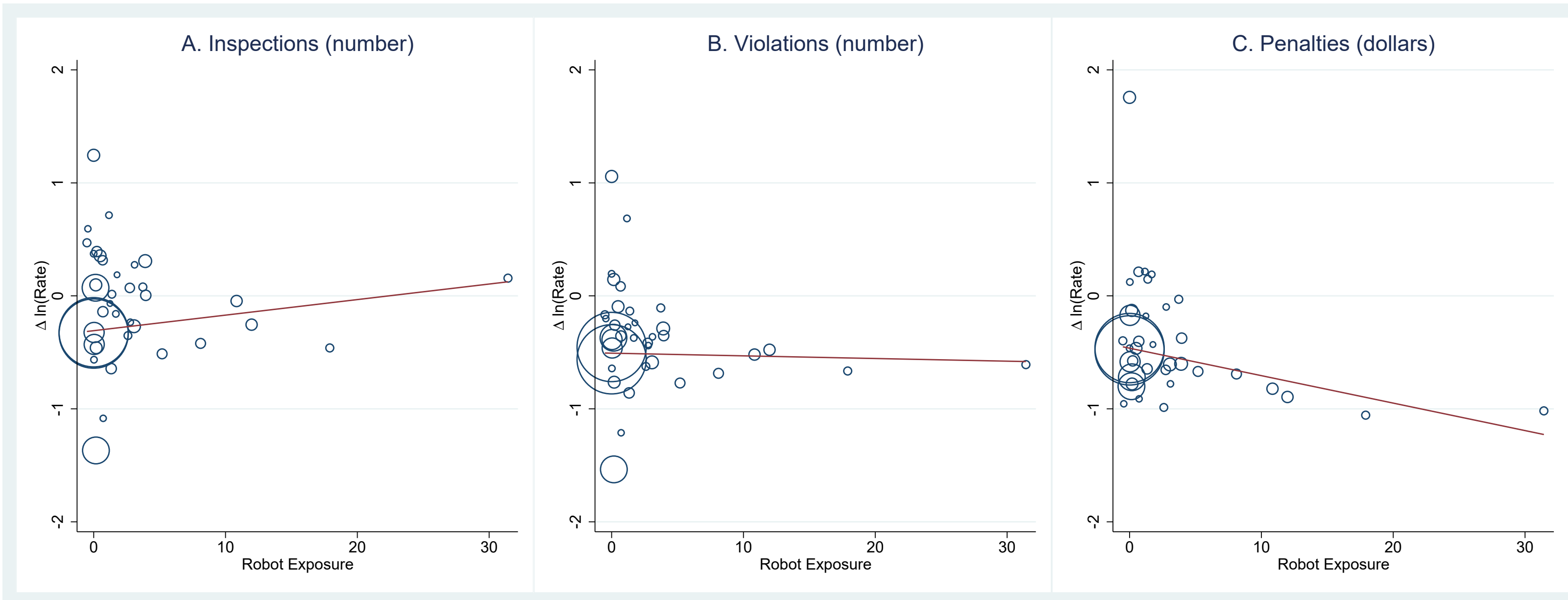
Each marker corresponds to an industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The marker size is proportional to employment data from the County Business Patterns. The exposure to robots is measured as the number of robots per 1,000 workers by industry in five European countries, including Denmark, Finland, France, Italy, and Sweden. The workplace safety figures are differenced in logs between 1993 and 2000 and 2000 to 2007, and the exposure to robot figures are differenced in levels during the same periods.

Figure 5: Workplace Safety and Robot Exposure by Industry, Safety Pre-Trend 1986 to 1993 relative to Exposure 1993 to 2007



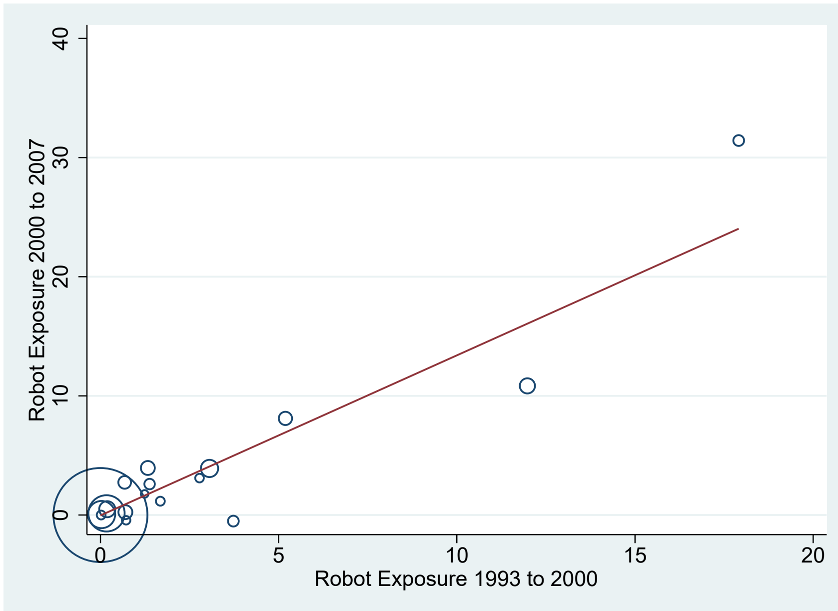
Each marker corresponds to an industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The BLS TRC (total recordable case) rate is the number of workplace injuries and illnesses per 100 full-time equivalent workers. The OSHA accident rate is the number workers involved in an OSHA-inspected accident per 100,000 workers. The marker size is proportional to employment data from the County Business Patterns. The exposure to robots is measured as the number of robots per 1,000 workers by industry in five European countries, including Denmark, Finland, France, Italy, and Sweden. The workplace safety figures are differenced in logs between 1986 and 1993, and the exposure to robot figures are differenced in levels between 1993 to 2007.

Figure 6: Inspections, Violations, and Penalties and Robot Exposure by Industry, Stacked Differences 1993 to 2000 and 2000 to 2007



Each marker corresponds to an industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The OSHA inspection and violation rates are the number per 1,000 establishments, and the penalty is the amount in 2020 dollars per 1,000 establishments. The number of establishments are tabulated from the CBP. All three measures are calculated using a three-year lead average. The marker size is proportional to employment data from the County Business Patterns. The exposure to robots is measured as the number of robots per 1,000 workers by industry in five European countries, including Denmark, Finland, France, Italy, and Sweden. The inspection figures are differenced in logs between 1993 and 2000 and 2000 to 2007, and the exposure to robot figures are differenced in levels during the same periods.

Figure 7: Inspections, Violations, and Penalties and Robot Exposure by Industry, Stacked Differences 1993 to 2000 and 2000 to 2007



Each marker corresponds to an industry as defined by the International Federation of Robotics (IFR), excluding agriculture. The exposure to robots is measured as the number of robots per 1,000 workers by industry in five European countries, including Denmark, Finland, France, Italy, and Sweden.