Automation and Diverging Health Risks*

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Abstract

This paper examines the impact of automation on workers' health risks, using occupational injury and hospitalization data. We first document that automation leads to a divergence in the severity of occupational health risks. Utilizing data on nonfatal and fatal workplace injuries, we show that while automation reduces nonfatal occupational injury incidence, it increases fatal occupational injury incidence. Secondly, the disparity of health risks across age groups has widened due to automation. Hospital discharge data suggests that overall hospitalizations due to injuries and despair-related conditions (e.g., substance abuse) have declined in commuting zones with higher automation exposure. Yet, the benefits are concentrated among young workers, while middle-aged workers exposed to automation experience increased hospitalizations, particularly due to despair-related conditions. Combining the empirical estimates of nonfatal and fatal injury incidence, a back-of-the-envelope calculation suggests that workplace automation overall provides significant, health-driven economic benefits. However, the rise in fatal injuries offsets between 14% and 27% of economic benefits from the reduction of nonfatal injuries. In summary, automation improves workplace safety on average, but it shifts the distribution of accidents away from minor injuries towards high-impact failures and disproportionately reduces hospitalizations for younger workers while potentially increasing risks for older workers.

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1 Introduction

Automation is one of the most significant and rapidly growing technological advancements, transforming industries and reshaping labor markets. Since the 1990s, the use of industrial robots has surged globally. The United States, ranking third worldwide in robot stocks as of 2022, has seen a dramatic increase in automation, with an eight-fold rise in robots per manufacturing worker over the past three decades (Acemoglu et al., 2023; International Federation of Robotics, 2024). This technological development has wide-ranging effects on workers and their work arrangements, and consequently their health through various channels. While it may reduce physical burden on workers, it can create additional, potentially more severe risks, both physically and mentally. Further, the effects may be heterogeneous, if some individuals find it more challenging to adjust to the new technology.

Given these multifaceted effects of automation, a comprehensive analysis of its impact on worker health is essential. This paper seeks to provide such an assessment by examining a range of health outcomes, including nonfatal and fatal occupational injuries, and hospitalizations by diagnoses. While previous studies have explored some of these issues (e.g., Gihleb et al. 2022; Gunadi and Ryu 2021; O'Brien et al. 2022), our work is one of the first studies to measure automation's impact on fatal occupational injury incidence and to analyze diagnosis-specific hospitalizations that include both physical and mental conditions, and their heterogeneous effects.

Our empirical strategy exploits the geographical variations in industrial robot exposure to identify the health effects of automation. Specifically, we construct a Bartik-style measure of robot exposure, which captures the intensity of robot adoption weighted by the industrial composition of local labor markets, using the industrial robot stock data from the International Federation of Robots (IFR). To address potential endogeneity concerns, we employ a shift-share instrumental variable (SSIV) approach. Following Acemoglu and Restrepo (2020), our SSIV is constructed using pre-automation industry compositions in US local labor markets and robot adoption in European countries that were ahead of the US in robotization. Due to data limitations, our baseline analysis relies on reduced-form estimation; however, robustness checks, including two-stage least squares (2SLS) estimates, confirm the consistency of our findings and their implied magnitudes.[1]

We explore the effects of automation on three outcomes: nonfatal occupational injury from the Survey of Occupational Injuries and Illnesses (SOII) data; fatal occupational in-

[1]The IFR contains industry-level robot stock data for European countries starting in 1993, but for the US, only starting in 2004. A reduced-form approach allows for a longer sample period.

jury from the Census of Fatal Occupational Injuries (CFOI) data; and diagnosis-specific hospitalizations from the Nationwide Inpatient Sample (NIS) data of the Healthcare Cost and Utilization Project (HCUP). As the occupational injury data are reported at the state level, we construct automation measures at the state level for the first two analyses. For the hospitalization analysis, we use the hospital county code in the NIS that allows us to conduct the analysis at the commuting zone (CZ) level. Following the recent literature on SSIV analyses (e.g., Borusyak et al., 2022), we conduct regional balance tests at the state and commuting zone levels to validate our empirical approach.

We summarize our findings as follows. First, we find a divergence in the severity of occupational risks workers face. The analysis of SOII suggests that a 10% increase in robot exposure decreases nonfatal injury per 1,000 full-time equivalent (FTE) workers by 0.9%, with the largest decline in injuries involving days of job transfer and restrictions. In contrast, the CFOI analysis implies a 1.3% increase in fatal injury per 100,000 FTE workers from a 10% increase in robot exposure. Among fatalities by sources, we find significant effects from 'tools, instruments, and equipment' (e.g., non-powered or powered hand tools, ladders, equipment) among others, suggesting that robots may indeed be influencing the outcomes. This finding also aligns with descriptive studies and anecdotal evidence of fatalities at workplace caused by robots.[2] However, our study is the first to present causal estimates and quantify its magnitude.[3] These two workplace injury analyses therefore imply that automation at workplace may have reshaped the severity of occupational health risks: while automation helped reduce nonfatal injuries, it may have increased incidence of more serious, fatal injuries.

Second, we find that increased exposure to automation reduces hospitalizations due to injuries and "despair"-related conditions; however, effects vary by age group, race, and sex. Consistent with findings from nonfatal occupational injuries, our analysis suggests that a 10% increase in robots lowers hospitalizations due to injuries by 2.4%.[4] In addition,

[2]For example, Layne (2023) identified 41 robot-related fatalities by manually reviewing narrative texts in the CFOI restricted-access research files between 1992 and 2017. Similarly, Kim et al. (2021) found that 6 out of 203 accidental deaths that occurred during maintenance in the manufacturing industry in South Korea between 2014 and 2018 were caused by robots. Additionally, there have been reports of worker deaths by industrial robots at an automotive factory in Texas (Ivanova, 2023) and at a vegetable packaging company in South Korea (Kim, 2023).

[3]Li and Singleton (2023) studies fatalities, using data from Occupational Safety and Health Administration (OSHA) inspections of work-related fatalities or hospitalizations. However, OSHA inspections only cover accidents that result in fatalities or hospitalizations of three or more employees. Thus, the data does not provide a comprehensive count of worker fatalities.

[4]NIS does not report whether the incident occurred at workplaces. Since most employed individuals are insured by employer sponsored health insurance (particularly more so, during our sample period, predating the Affordable Care Act), we check the effect among those whose primary payer is private. The estimated effect of automation is significant at 1.9% in the subsample. Further, we discuss in Section 4.4 that

we find reduced hospitalizations from mental disorders and "despair"-realted conditions à la Case and Deaton (2017) (e.g., alcohol and substance abuses). These aggregate effects, however, mask a large heterogeneity across worker demographics. For various diagnoses, from physical injuries to mental health conditions, we find that the benefits of automation are concentrated among young workers, while those over 45, white, and male workers tend to be adversely affected. Notably, the negative mental health impacts for these groups align with Albinowski and Lewandowski (2024), who find that automation disproportionately reduces labor demand for older workers. These findings suggest that automation has widened the disparity in health risks—both physical and mental—across worker demographics, particularly among different age groups.

The occupational injury analyses reveal opposing effects of automation on health risks. We integrate these estimates to conduct a back-of-the-envelope calculation, quantifying the net health benefits or costs of automation at workplaces. Between 1996 and 2010, our estimates imply an annual decrease of approximately 33,000 nonfatal injuries, amounting to $1.9 billion (2023 USD) in savings, based on value of statistical injury estimates. On the other hand, worker fatality increased by 42 annually, that result in between $262 and $516 million in losses based on estimates of the value of statistical life. These together imply that automation had net economic health benefits at workplaces, but that the burden of fatal injuries offsets between 14% and 27% of the nonfatal injury benefits.

Our empirical findings highlight the need for policies that aim at preventing workplace injuries, particularly severe and fatal ones. Enhancing safety training to keep pace with rapidly-evolving technology would be a crucial preventive measure for both workers and firms. On the worker side, expanding social insurance programs, such as Workers' Compensation program, to help support workers suffering from both physical and mental health conditions may also be welfare-improving.

Related Literature. This paper contributes to the extensive literature on the effects of automation. Numerous studies have examined how automation affects various outcomes such as employment and wages (e.g., Acemoglu and Restrepo, 2020), labor productivity (e.g., Graetz and Michaels, 2018), and family behaviors (e.g., Anelli et al., 2021).

Recently, there has been a growing body of work focusing on health outcomes of workers (e.g., Gunadi and Ryu, 2021; Gihleb et al., 2022; Liu et al., 2024b; Lu and Fan, 2024). We complement this literature in several ways. First, our paper is among the first to examine the impact of automation on fatal workplace injuries. A related study by O'Brien et al. (2022) examines mortality outcomes and their causes using death certificate data from the

quantitative magnitudes from occupational injuries and injury-driven hospitalizations are comparable.

US National Center for Health Statistics.[5] While their analysis provides insights into the impact of automation on a range of mortality causes, the data's ability to directly link mortality to workplace incidents is limited—a gap that our work addresses. Our work, along with previous studies such as Gihleb et al. (2022), demonstrates a decrease in nonfatal workplace injuries due to automation. Relatedly, Li and Singleton (2023) finds positive but statistically insignificant effect of automation on workplace fatalities. Their analysis, however, is based on OSHA inspections data, which only include fatalities from accidents involving three or more employees in an establishment. Thus, the data undercounts workplace fatalities. The novel finding of increased fatal occupational injuries, despite a reduction in nonfatal injuries, highlights the need to assess the impact of automation on broader spectrum of injury severity. Second, we evaluate the effects on diagnosis-specific hospitalizations, which provides a more objective measure of health outcomes than self-reported health status (e.g., Gunadi and Ryu, 2021; Liu et al., 2024b), and a less drastic outcome relative to e.g., mortality (e.g., O'Brien et al., 2022).[6] In these analyses, we further uncover varying effects of automation across worker demographics, an aspect that previous studies have not explored.

Our paper also speaks to the large literature on the health consequences of exposure to economic shocks. In addition to studies on industrial robot adoption, there have been papers that examine the health effects of recessions (e.g., Ruhm 2000; Hollingsworth et al. 2017), job loss (e.g., Eliason and Storrie 2009; Kuhn et al. 2009; Sullivan and von Wachter 2009; Browning and Heinesen 2012; Ahammer et al. 2023), and trade shock (Autor et al., 2019; Lang et al., 2019; Adda and Fawaz, 2020; Pierce and Schott, 2020; Lai et al., 2022; Kim et al., 2024). We contribute to this strand of literature by providing new evidence regarding the effects of major technology and labor market shocks on health. While automation shares some characteristics with other shocks like import competition, it also uniquely offers the potential to support workers in completing specific tasks, thus potentially mitigating the negative consequences from worker displacement documented in Acemoglu and Restrepo (2020). Our estimates on various outcomes capture these diverse channels through which automation impacts workers' health risks.

Lastly, this paper relates to studies on determinants of workplace safety. Previous stud-

[5] O'Brien et al. (2022) shows that automation is associated with an increase in deaths due to drug overdose and suicide among those aged 45–54. On a similar note, Gihleb et al. (2022) also finds an increase in drug- or alcohol-related mortality from Behavioral Risk Factor Surveillance System (BRFSS). These results are consistent with our finding: increased hospitalizations due to despair-related conditions among middle-aged workers.

[6] Gunadi and Ryu (2021) finds an improvement in self-reported health and a reduction in disability among low-skilled individuals.

ies have examined the effects of various factors, including workers' compensation (e.g., Ruser 1985; Moore and Viscusi 1989; Krueger 1990; Johnson et al. 2024), minimum wage (Davies et al., 2024; Liu et al., 2024a), import competition (McManus and Schaur, 2016), labor unions (Li et al., 2022) and firms' financing constraints (Cohn and Wardlaw, 2016). Our study extends this literature by highlighting the impact of technological change on workplace injuries.

The rest of the paper is organized as follows. In Section 2, we describe data sources we use in this study. Section 3 discusses the measure of robot exposure and the empirical strategy. Section 4 presents the results on nonfatal and fatal injuries and hospitalizations, followed by discussions of the quantitative and policy implications of our findings in Section 5.

2 Data

In this section, we outline the data sources, beginning with the automation data and datasets for three outcome variables: nonfatal injuries, fatal injuries, and hospitalizations. We then provide descriptive statistics of outcome variables.

2.1 Industrial Robots: IFR

An industrial robot is defined by International Federation of Robotics (IFR) as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications." We use data on industrial robot stock provided by the IFR, which collects this information directly from nearly all major industrial robot producers and national robotics associations.

The IFR data covers over 50 countries from 1993 to 2017 and includes the operational stock of robots, defined as "the number of robots currently deployed," for each country and year. The dataset provides information on robot stock across seven broad sectors: agriculture, forestry, and fishing; mining and quarrying; manufacturing; utilities; construction; education, research, and development; and other services (all other non-manufacturing branches, such as wholesale and retail trade; accommodation and food service; and financial services). Within the manufacturing sector, data are available for 13 more detailed subsectors: food and beverages; textiles (including apparel); wood and furniture; paper and printing; plastics and chemicals; minerals; basic metals; metal products;

industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing.[7] Throughout the paper, we refer to this sector classification as the "IFR industries."

The industry-level robot stock data in the 1990s are available only for Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. For the United States, industrial-level data are available starting from 2004, while total robot stocks are available from 1993 onward. Due the data limitation, we utilize the industry-level European robot stocks in earlier years to conduct our empirical analysis, as we discuss in Section 3.

2.2 Nonfatal Workplace Injuries: SOII

We use state-level data on nonfatal workplace injuries from the Survey of Occupational Injuries and Illnesses (SOII), provided by the Bureau of Labor Statistics (BLS). The SOII data is available from 1995 to 2022, but lacks information for six states: Colorado, Idaho, Missouri, New Hampshire, North Dakota, and South Dakota. Additionally, for specific years, data is unavailable for eleven additional states and the District of Columbia.[8]

The data covers work-related injuries or illnesses requiring medical treatment beyond basic first aid.[9] It is based on employers' annual reports submitted to the BLS, which include information on work-related injuries and illnesses, average annual employment, and the total hours worked by all employees. The data contains both the number and rate of incidence, with the incidence rate defined as the number of injuries per 100 full-time equivalent (FTE) workers. The injuries are classified into several types: cases with days away from work (DAWF), cases with days of job transfers or restriction (DJTR), and cases without lost workdays (other recordable cases). When a case involves both DAFW and DJTR, the case is recorded as DAWF. Other recordable cases involve medical treatment beyond first aid but not DAFW or DJTR.

[7] Approximately 30% of robots are not assigned to a specific industry. Following the approach of Acemoglu and Restrepo (2020), we allocate the unclassified robots to industries in proportion to the classified ones to address this issue.

[8] The missing states (years) are: Arizona (1995), District of Columbia (up to 2003), Florida (2011 onwards), Illinois (up to 1997), Massachusetts (2009), Ohio (up to 2011), Pennsylvania (up to 2010), Rhode Island (2008 onwards), South Carolina (1995), Vermont (up to 1996), West Virginia (up to 1997), and Wyoming (up to 2001).

[9] It excludes work-related fatalities, nonfatal injuries and illnesses involving self-employed individuals, workers on farms with 10 or fewer employees, private household workers, volunteers, and federal government employees.

2.3 Fatal Workplace Injuries: CFOI

State-level data on fatal injuries is from the Census of Fatal Occupational Injuries (CFOI). BLS collects this data using various sources such as death certificates, news media reports, workers' compensation reports, and OSHA reports.

CFOI data is available from 1992 to 2021, covering all 50 states and the District of Columbia. Fatal injuries are only available as counts, unlike nonfatal injuries, which are reported both as counts and rates. For comparability across states, we construct a measure of fatal injuries per 100,000 FTE workers, in a way similar to the BLS methodology for calculating nonfatal injury rates. This measure is derived using state-level total hours worked data, calculated from the monthly Current Population Survey.[10]

The dataset also provides the source of fatal injury in eight categories: chemicals; containers and furniture; machinery; parts and materials; tools; structures and surfaces; persons, animals, and plants; vehicles (see Table A.1 for details and examples). Additionally, the injury statistics by age groups, race, and sex are available.

2.4 Hospital Discharge by Diagnoses: HCUP NIS

We use hospitalization data for years 1993 to 2011 obtained from the Nationwide Inpatient Sample (NIS) of the Healthcare Cost and Utilization Project (HCUP) from the Agency for Healthcare Research and Quality (AHRQ). The NIS is the "largest publicly available all-payer inpatient care database in the United States, containing data on more than seven million hospital stays" (AHRQ, 2024). It includes all discharges from a 20% random sample of US community hospitals, drawn each year from each stratum.[11] During the sample period, our sample includes 31 states.[12]

This dataset provides detailed information on patients such as their underlying conditions by ICD-9-CM (International Classification of Diseases - 9th revision - Clinical Modification) code, age, sex, and median income based on the patient's ZIP Code. It also

[10] Specifically, the state fatal injury rates are calculated as $(N_{st}/EH_{st}) \times 2,000 \times 100,000$ where N_{st} denotes the number of fatal work injuries, and EH_{st} represents the total hours worked by all employees in state s and year t. $2,000 \times 100,000$ represents the base for 100,000 FTE workers, assuming they work 40 hours per week for 50 weeks in a year.

[11] The strata are defined by geographic region (Northeast, Midwest, West, and South), hospital control (public, private not-for-profit, and private investor-owned), location (urban and rural), teaching status, and bed size. Due to this sampling scheme, aggregating hospitalizations at geographic levels lower than these regions does not necessarily yield representative estimates.

[12] No data is available in the NIS for nine states (Alabama, Arkansas, Delaware, District of Columbia, Idaho, Louisiana, New Mexico, Oklahoma, and Wyoming). Additionally, 11 states (Georgia, Hawaii, Indiana, Kansas, Michigan, Nebraska, Ohio, South Carolina, South Dakota, Tennessee, and Texas) cannot be used due to the absence of detailed geocodes (zip codes or county FIPS codes).

includes hospital information, such as hospital identifiers, county code, ownership, and (categorized) bed size. The availability of hospital county code is crucial for our analysis as we utilize the geographical variation in automation exposure to estimate its effects on hospitalizations.[13]

As we are interested in the effects of automation in workplaces, we restrict our sample to discharges of individuals in the working age, between the ages of 18 and 65. Subsequently, we calculate the number of discharges for each condition in cells defined by cohort, sex, and hospital, using discharge weights provided by HCUP.[14]

2.5 Descriptive Statistics of Outcome Variables

For our analysis, we restrict sample years to 1996 through 2010 for consistency across outcome variables. Additionally, nonfatal and fatal occupational injury analyses use 33 states of balanced panel.[15] The descriptive statistics for the outcome variables are documented in Tables 1 and 2 for injuries and discharges, respectively.

In Table 1, we report statistics for nonfatal and fatal injuries—the mean, standard deviation and the 25th, 50th, and 75th percentiles of the distributions—spanning 1996 to 2010 (15 years) across 33 states in our sample. The average nonfatal injuries is around 5 per 100 FTE workers, with about half of them not involving any lost workdays. The other half of the injuries are categorized as requiring job transfers or restrictions, or days away from work. For fatal injuries, the average is about 4 in 100,000 FTE workers and their sources vary, with the largest share from vehicles. The age and sex differences in injury incidence rates are also significant: the male incidence is higher, and older individuals, specifically those older than 55, have higher incidence rates.

Table 2 documents the discharge statistics by diagnoses that are more likely to be influenced by automation physically (e.g., injury and backaches) or mentally (e.g., substance and opioid abuse).[16] The data contains hospitals of various sizes, with 25th and 75th percentiles of admissions at 2,700 and 27,000, respectively. The average discharges from in-

[13]The discharge data is also available post-2012 and is referred to as the National Inpatient Sample. Starting in 2012, however, HCUP changed the sampling methodology. Instead of sampling hospitals (where all hospitalizations from sampled hospitals were included), they began sampling discharges directly. This shift means that post-2012 data no longer allow for hospital-level aggregates of hospitalizations. Thus, we limit the NIS sample to data from 2011 and earlier.

[14]The cohort is divided into five groups based on birth years: before 1940, 1940s, 1950s, 1960s, and 1970 or later.

[15]Using all available states do not impact our results, which are presented in Appendix A.3 as a robustness check.

[16]The mapping between diagnoses and ICD-9-CM codes and summary statistics of discharges by other diagnoses (e.g., neoplasm and heart problems) are included in Appendix A.1.

Table 1: Summary Statistics of Nonfatal and Fatal Injuries

		Mean	SD	P25	P50	P75
Nonfatal injury (*per 100 FTE workers*)		5.16	1.66	3.90	4.90	6.10
by type	w/o lost workdays	2.56	0.99	1.80	2.30	3.10
	w/ days of transfer/restriction	1.06	0.45	0.80	1.10	1.30
	w/ days away from work	1.54	0.47	1.20	1.50	1.80
Fatal injury (*per 100,000 FTE workers*)		4.35	1.63	3.01	4.18	5.32
by source	Tools, instruments, & equipment	0.07	0.08	0.00	0.08	0.11
	Machinery	0.34	0.19	0.20	0.30	0.46
	Parts and materials	0.28	0.16	0.19	0.25	0.36
	Chemicals & chemical products	0.08	0.10	0.00	0.08	0.12
	Vehicles	1.91	1.01	1.22	1.76	2.34
	Containers	0.04	0.06	0.00	0.00	0.06
	Structures and surfaces	0.62	0.23	0.49	0.59	0.72
	Persons, plants, animals, & minerals	0.20	0.17	0.10	0.15	0.27
by age	24 and younger	3.66	1.81	2.58	3.44	4.57
	25-34	3.37	1.66	2.32	3.21	4.17
	35-44	3.64	1.59	2.64	3.40	4.40
	45-54	4.12	1.78	2.89	3.90	5.09
	55-64	5.58	2.69	3.68	5.09	6.93
	65 and older	16.18	10.41	8.75	13.52	21.02
by race	White	4.33	1.70	2.94	4.10	5.36
	Non-white	4.50	2.90	3.10	4.08	5.33
by sex	Male	6.99	2.62	4.84	6.72	8.46
	Female	0.76	0.42	0.49	0.68	0.95
Observations				495		

Note: The nonfatal injury data is from the SOII, and the fatal injury data is from the CFOI. The sample is for 33 states and years 1996-2010, and statistics are weighted by state employment.

juries are relatively fewer than those from mental disorders or “despair”-related diseases, as defined in Case and Deaton (2017) that include alcohol, substance, and opioid abuses, and suicide attempts.

3 Empirical Analysis

Our empirical strategy is to utilize geographical variations in automation exposure to estimate the health effects. In this section, we first discuss how we measure the exposure to industrial robots. Depending on the available data for outcome variables, we consider robot exposure measures at different geographic levels: a state-level measure for the occu-

Table 2: Summary Statistics of Hospital Discharges by Diagnosis (per Hospital)

		Mean	SD	P25	P50	P75
All admissions		20,002.9	25,677.5	2,719.9	10,865.1	27,453.8
by diagnosis	Injury	767.6	1,394.5	69.8	324.6	775.7
	Backache	76.2	156.6	0.0	15.8	83.9
	Mental disorders	5,937.0	8,294.4	538.0	2,749.4	7,978.3
	Despair-related	3,430.4	6,109.5	192.5	1,099.7	4,095.0
	Alcohol abuse	1,452.4	2,327.1	109.8	552.1	1,877.2
	Substance abuse	1,220.5	2,470.5	33.8	270.0	1,303.5
	Opioid abuse	485.9	1,264.8	11.9	89.0	397.2
	Suicide attempt	271.5	395.8	19.7	123.9	358.2
Observations				9,950		

Note: The data is from the 1996-2010 NIS.

pational nonfatal and fatal injury analyses, and a commuting-zone (CZ)-level measure for the hospitalization analyses. We then specify the estimating equation and present regional balance test results to check the validity of our approach.

We construct a Bartik-style measure of robot exposure, representing the intensity of robot adoption weighted by the geographical industrial composition as follows:

$$\text{Robot}_{gt}^{\text{US}} = \sum_{i \in \text{Manuf}} \ell_{igt}^{\text{US}} \cdot \frac{M_{it}^{\text{US}}}{L_{it}^{\text{US}}} \tag{1}$$

where ℓ_{igt}^{US} is industry i's share in total employment of geographic region g in year t. M_{it}^{US} and L_{it}^{US} are robot stocks and total employment in industry i in the US in year t (in 1,000 workers), respectively.[17] Thus, the measure $M_{it}^{\text{US}}/L_{it}^{\text{US}}$ captures the intensity of robot adoption in industry i, and $\text{Robot}_{gt}^{\text{US}}$ reflects the exposure of region g to automation weighted by the industry's share in the region's employment. The region with a higher concentration of employment in robot-intensive industries is assigned a higher value of this measure, indicating greater exposure to automation.

Using the robot exposures, we investigate the effects of industrial robots on occupational injuries at the state level by estimating the following equation:

$$y_{st} = \delta_0 + \beta \cdot \text{Robot}_{st}^{\text{US}} + \delta_X \cdot X_{st} + \delta_s + \delta_t + \epsilon_{st}, \tag{2}$$

[17] To compute ℓ_{igt}^{US} and L_{it}^{US}, we use the monthly Current Population Survey (CPS; Flood et al., 2024) for the state-level measure and the County Business Pattern (CBP) for the CZ-level measure. We rely on the version processed by Eckert et al. (2020) due to the suppression of small industry-county cells in the original CBP data.

where y_{st} represents workplace injuries (per 100 FTE workers for nonfatal and per 100,000 FTE workers for fatal injuries) in state s in year t. The automation exposure is captured by $\text{Robot}_{st}^{\text{US}}$ and our coefficient of interest is β. We include δ_s and δ_t that capture state- and year-fixed effects, respectively, and a vector of control variables, X_{st}. These include state demographic characteristics, such as the share of sex, race, and age groups, and macroeconomic characteristics such as the unemployment rate, shares of manufacturing and light manufacturing in employment, and the share of females in employment.[18] Additionally, we include a Bartik measure of exposure to imports from China at the state level, as defined in Autor et al. (2013) to control for potential confounding effects of trade competition, as previous studies report its detrimental effects on workplace injuries (Lai et al., 2022). We cluster standard errors at the state level.

Next, to examine the effects of robot exposure on hospitalization at the CZ level, we estimate the following model:

$$y_{ahct} = \delta_0 + \beta \cdot \text{Robot}_{ct}^{\text{US}} + \delta_X \cdot X_{ct} + \delta_a + \delta_h + \delta_t + \epsilon_{ahct}, \tag{3}$$

where y_{ahct} denotes the $\log$ number of hospitalizations plus one for cohort $\times$ sex cell a in hospital h, located in CZ c in year t. $\text{Robot}_{ct}^{\text{US}}$ represents robot exposure in CZ c in year t. We control for fixed effects of cohort-by-sex cells δ_a, hospitals δ_h, and years δ_t; and the vector X_{ct} includes time-varying CZ-level controls, analogous to the variables used in the state-level regressions. In addition, X_{ct} includes (log) population to account for any change in population over time, as our outcome variable is the number of hospitalizations.[19] Standard errors are clustered at the CZ level.

Identification. Using the robot exposure measure defined in Equation (1) to estimate its health effects, however, may be subject to reverse causality or omitted-variable biases, as it may be correlated with unobserved shocks or characteristics in a region that may affect the labor market and health outcomes. For example, regions with high fatal injury rates may be more likely to adopt robots as a means to improve workplace safety. To address this endogeneity issue, we employ a shift-share instrument, following Acemoglu and Restrepo (2020). Specifically, we construct the instrument using 1970 industry shares in the US and the average robot adoption of five European countries—Denmark, Finland, France, Italy, and Sweden (referred to as "EURO5")—which exhibit higher robot adoption than the US.

[18]Light manufacturing industries include textile, and paper and printing industries. The summary statistics of state and commuting-zone level characteristics and their descriptions are relegated to Appendix A.1.

[19]Due to HCUP's sampling scheme mentioned in footnote 11, we are not able to construct a consistent measure of hospitalization rates (e.g., hospitalizations per population) for CZs or states.

This approach captures variation driven by global technological advancements in robotics, which are not likely to be affected by economic or policy conditions specific to the US.[20] The instrument is defined as follows:

$$\text{Robot}_{gt}^{\text{IV}} = \sum_{i \in \text{Manuf}} \ell_{ig,1970}^{\text{US}} \cdot \left(\frac{1}{5} \sum_{j \in \text{EURO5}} \frac{M_{it}^{j}}{L_{i,1970}^{j}} \right). \tag{4}$$

The variables M_{it}^{j} and $L_{i,1970}^{j}$ measure country j's the robot stock and total employment in industry i in years t and 1970, respectively.[21] The term $\ell_{i,g,1970}^{\text{US}}$ measures the industry employment *share* in 1970 in region g, derived from the Census data (Ruggles et al., 2024). The second term, the average robot adoption of five European countries for each IFR industry relative to the 1970 employment, represents the set of *shifters* (or *shocks*). We show in Figure A.2 (Appendix A.1) that EURO5 robot adoption is closely associated with US robot adoption at the industry level, with an R-squared of 0.8, mitigating concerns about a weak instrument.[22]

The recent shift-share instrument literature highlights that identification in shift-share designs depends on the exogeneity of either the shocks or the shares (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). In our context, the shocks—robot adoption in European countries—are arguably orthogonal to unobservable local factors impacting industry-level robot adoption, as they capture variation driven by global technological advances in robotics. More advanced and cost-effective robots would lead to increased adoption in both Europe and the US, while European adoption would remain unaffected by the US-specific economic or policy factors. Additionally, the industry's share of employment in 1970 in a region is also exogenous. Since it predates US robotization, the 1970 industry employment share is unlikely to correlate with current local shocks that affect workplace safety and hospitalizations.

In constructing the IV, we restrict the set of shares to manufacturing industries for the following reasons. First, the IFR data includes robot stocks classified by two-digit manufacturing industry codes, enabling a more precise measurement of automation at a disaggregated industry level. Second, an additional identification condition in shift-share designs is that the inverse normalized Herfindahl-Hirschman Index (HHI) of average shock exposure should be sufficiently large; equivalently, the normalized HHI should be close

[20]Germany is excluded as its robot adoption is far ahead of the US, potentially making it less relevant (see Figure A.1). Similarly, Norway, Spain, and the UK are not included, as their robot adoption lags behind that of the US.

[21]The employment data for European countries is from EU KLEMS (O'Mahony and Timmer, 2009).

[22]While we use robot stocks in five European countries as the baseline following Acemoglu and Restrepo (2020), Tables 7 and 8 show that our findings are robust to using an alternative choice of countries.

to zero (Borusyak et al., 2022). Specifically, the inverse normalized HHI is expressed as $1/\sum_{it}(\hat{\ell}^{\text{US}}_{i,1970})^2$, where $\hat{\ell}^{\text{US}}_{i,1970}$ is derived by normalizing $\ell^{\text{US}}_{i,1970}$ to sum to one across industries and years. In our case, the other services in IFR industries accounts for 56% of 1970 employment, yielding an inverse HHI of 45. To address this, we exclude this sector, resulting in an inverse HHI of 168.[23]

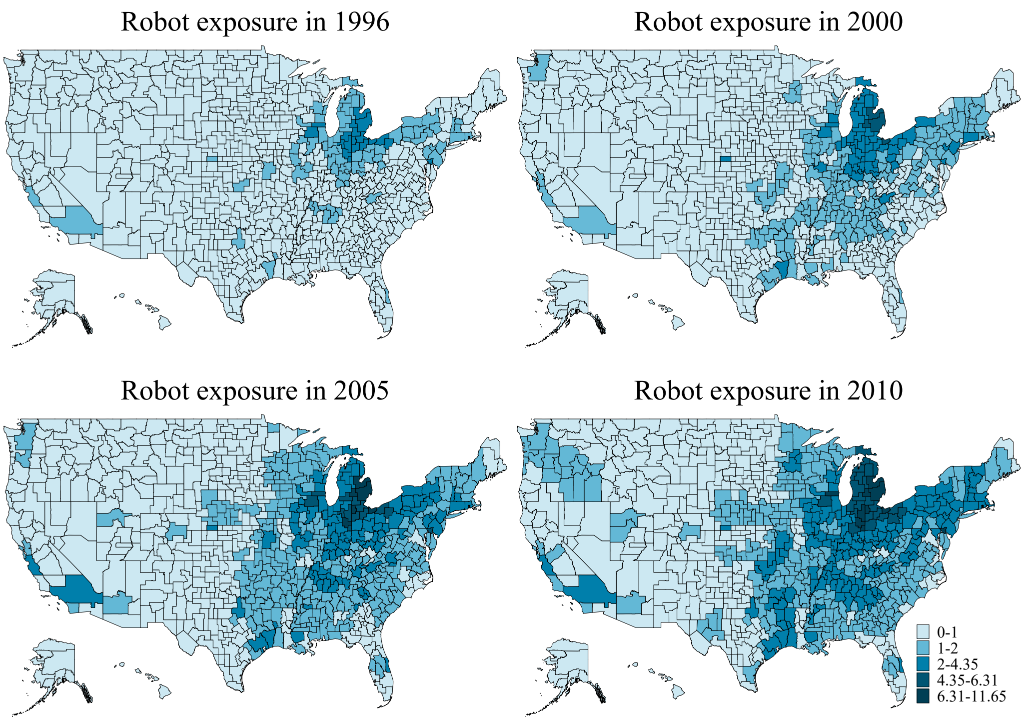


Figure 1: Robot Exposures

Note: This figure presents the CZ-level robot exposure measures, as defined in Equation (4), for years 1996, 2000, 2005, and 2010.

In Figure 1, we map robot exposures as measured by Equation (4) at the commuting-zone level for years 1996, 2000, 2005, and 2010. There are both large temporal and geographical variations in automation exposure. Across commuting zones (states), the average robot stocks in our sample is 1.49 (1.74) per 1,000 workers with the standard deviation of 0.89 (1.42) and the median of 1.32 (1.45). While the averages are similar across commuting zones and states, the standard deviation is larger in the state-level data, reflecting greater diversity across states than more localized commuting zones. During our sample

[23]We perform robustness analyses on this choice in Section 4.4. As shown in Tables 7 and 8, including all sectors in the construction of the robot measure and instrument does not impact our results.

period, robot stocks increased by 1.15 per 1,000 workers on average, which translates to a 6.42% annual growth rate.

In our baseline analyses, we estimate reduced-form regressions of outcomes on the instrumental variable. Since detailed industrial robot data for the US before 2004 are unavailable in the IFR dataset (as noted in Section 2), the exposure measure defined in Equation (1) is restricted to the post-2004 period. However, limiting the sample to 2004 and later substantially reduces statistical power (particularly for state-level analyses of occupational injuries). At the same time, estimating two-stage least squares (2SLS) over a longer period would require making a strong assumption to impute the pre-2004 US robot stock. To avoid this, we follow Acemoglu and Restrepo (2020) and report reduced-form estimates as our baseline. As robustness checks, we show that alternative estimations and specifications, including 2SLS estimates using post-2004 data, produce results consistent with our main findings, both quantitatively and qualitatively.

Regional Balance Tests. Before discussing the main results, we conduct regional balance tests, as suggested by Borusyak et al. (2022), to examine whether our instrument is correlated with preexisting trends in the outcomes. A significant estimate would imply that regions more exposed to robot adoption between 1996 and 2010 might have already been experiencing differential trends in workplace injuries and hospitalizations between 1993 and 1996. Specifically, for workplace injuries, we regress changes in outcomes (in levels and percents) from 1993 to 1996 on changes in the IV (in levels and percents) from 1996 to 2010 at the state level. We conduct analogous analysis for hospitalization data at the CZ-level.[24]

Table 3 reports the results of our regional balance tests. Under both measures, we find no evidence that the shift-share instrument is systematically associated with pre-period outcomes, except for suicide attempts, which supports causal interpretation of our estimates.

4 Results

We now discuss the estimated effects of automation on nonfatal and fatal workplace injuries, and hospitalizations.

[24]For hospitalizations, because we are unable to construct a measure of CZ-level hospitalizations (see footnote 11), we adopt the following approach. We first calculate the per-hospital number of condition-specific hospitalizations for each CZ and year. Next, for each CZ, we compute annual changes in hospitalizations between the first and last years of the pre-period in which data is available since data is not available for every CZ in all years. We then regress these changes on changes in the IV between 1996 and 2010.

Table 3: Regional Balance Test of Outcomes

	Change in Robots, 1996-2010			
	(1) Level Coefficient (Standard Error)		(2) Percent Coefficient (Standard Error)	
Panel A: Workplace injury, change in outcomes 1993-1996				
Nonfatal injury	0.062	(0.077)	-0.002	(0.033)
Fatal injury	0.029	(0.085)	-0.077	(0.077)
Observations	33		33	
Panel B: Hospitalization, change in outcomes 1993-1996				
Total admissions	-1.018	(1.023)	-0.034	(0.037)
Injury	-0.061	(0.057)	-0.038	(0.048)
Backache	-0.003	(0.003)	0.016	(0.037)
Mental disorders	-0.022	(0.235)	-0.035	(0.050)
Despair-related	0.135	(0.213)	0.003	(0.067)
Alcohol abuse	-0.005	(0.080)	-0.022	(0.074)
Substance abuse	0.098	(0.089)	0.021	(0.081)
Opioid abuse	0.053	(0.044)	0.045	(0.054)
Suicide attempt	-0.012	(0.017)	0.126*	(0.075)
Observations	179		179	

Note: The data for Panel A is from SOII and CFOI, and for Panel B, HCUP NIS. This table presents coefficients from regressions of pretrends in the outcomes on the shift-share instrument. The unit of observation is the state in Panel A and the CZ in Panel B. We control for the sum of exposure shares, $\sum_{i\in\text{Manuf}} \ell^{\text{US}}_{i,s,1970}$, in Panel A, and for the sum of CZ-level exposure shares interacted with indicators for the first and last years of the pre-period in which CZs are observed in Panel B, following Borusyak et al. (2022). All regressions are weighted by the population of the first pre-period year in the sample. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.1 Automation and Nonfatal Occupational Injuries

In Table 4, we report the effects of automation on nonfatal injury incidence per 100 FTE workers. We present results with state and year fixed effects in column (1) and add various sets of state-level controls including demographic characteristics (column (2)), macroeconomic conditions (column (3)), and exposure to trade shock measured by import penetration per worker (column (4)). The mean of the outcome variable is also reported for ease of quantifying the effects.

We find that robot exposure led to a statistically significant decrease in nonfatal injury incidence, with its effects robust to adding various state-level demographic and economic controls. Our preferred specification in column (4) implies that a 10% increase in robot

Table 4: Automation and Nonfatal Workplace Injuries (per 100 FTE Workers)

	(1)	(2)	(3)	(4)	Mean
All nonfatal injuries	-0.454***	-0.407***	-0.242**	-0.261***	5.160
	(0.078)	(0.090)	(0.089)	(0.086)	
Nonfatal injuries by type					
Injury w/o lost workdays	-0.214***	-0.190***	-0.100	-0.110*	2.560
	(0.056)	(0.063)	(0.060)	(0.059)	
Injury w / days of job transfer or restriction	-0.196***	-0.178***	-0.146***	-0.148***	1.059
	(0.025)	(0.029)	(0.028)	(0.026)	
Injury w / days away from work	-0.039	-0.042	-0.016	-0.023	1.542
	(0.026)	(0.028)	(0.028)	(0.027)	
Demographics		✓	✓	✓	
Macroeconomic controls			✓	✓	
Import penetration				✓	
States	33	33	33	33	
Observations	495	495	495	495	

Note: The data is from the 1996-2010 SOII. This table presents estimates of the effects of industrial robot exposure on nonfatal injury incidence per 100 FTE workers. All regressions are weighted by the state employment. Standard errors clustered at the state level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

exposure from the mean (0.17 robots per 1,000 workers) decreases nonfatal injury rate by 0.9% (0.17×(-0.261)/5.160). Among nonfatal injuries, those involving days of job transfer and restriction have decreased the most at 2.4%.[25] These findings align qualitatively with prior literature; for example, Gihleb et al. (2022) report a 2.1% reduction in occupational injuries associated with a 10% increase in robot exposure, using on the OSHA Data Initiative for 2005–2011. Our results complement and further corroborate the beneficial effect of automation in reducing nonfatal injuries at workplace.

4.2 Automation and Fatal Occupational Injuries

Now, we turn to the effects of automation on fatal injury incidence at workplace. In Table 5, we present the effects on all fatal injuries per 100,000 FTE workers under various specifications consistent with those for nonfatal injury analysis. Across all specifications, we find that fatal injury incidence has increased due to automation with its coefficients

[25] While we investigate fatal injuries and hospitalizations across age, race, and sex, the available data on nonfatal injuries are insufficient for heterogeneity analyses.

ranging between 0.136 (column(2)) and 0.332 (column(4)). These effects translate into 0.02 (0.5%) and 0.06 (1.3%) more fatalities per 100,000 FTE workers due to a 10% increase in industrial robots.

Table 5: Automation and Fatal Workplace Injuries (per 100,000 FTE Workers)

	(1)	(2)	(3)	(4)	Mean
All fatal injuries	0.177*	0.136	0.295**	0.332**	4.354
	(0.089)	(0.097)	(0.130)	(0.123)	
Fatal injuries by source					
Tools, instruments, and equipment	0.013	0.011**	0.015**	0.015**	0.074
	(0.008)	(0.005)	(0.006)	(0.007)	
Machinery	-0.013	-0.015	0.000	0.004	0.341
	(0.016)	(0.019)	(0.025)	(0.024)	
Vehicles	0.131**	0.098	0.179**	0.195**	1.912
	(0.053)	(0.063)	(0.070)	(0.075)	
Parts and materials	0.007	0.009	0.004	0.010	0.280
	(0.008)	(0.011)	(0.015)	(0.015)	
Containers	-0.008	-0.011**	-0.001	-0.002	0.038
	(0.007)	(0.005)	(0.008)	(0.008)	
Structures and surfaces	0.015	0.015	0.022	0.025	0.615
	(0.012)	(0.017)	(0.027)	(0.027)	
Chemicals and chemical products	0.012	0.011	-0.009	-0.008	0.083
	(0.008)	(0.008)	(0.011)	(0.011)	
Persons, plants, animals, and minerals	0.023***	0.024**	0.026*	0.029**	0.200
	(0.008)	(0.009)	(0.014)	(0.014)	
Demographics		✓	✓	✓	
Macroeconomic controls			✓	✓	
Import penetration				✓	
States	33	33	33	33	
Observations	495	495	495	495	

Note: The data is from the 1996-2010 CFOI. This table presents estimates of the effects of industrial robot exposure on fatal injury incidence per 100,000 FTE workers. All regressions are weighted by state employment. Standard errors clustered at the state level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

There are several pathways in which automation may impact fatal injury incidence. The industrial robots could directly harm workers, as evidenced by incidents from an automobile factory where a factory robot attacked a worker (Ivanova, 2023), and a vegetable packaging plant where a robot crushed worker to death (Kim, 2023). On the other hand, if robots allow workers to avoid engaging in more dangerous or harmful tasks, it could have positive effects on fatal injury incidence. To further investigate the underlying causes of fatality, we utilize the source of injury data from the CFOI. CFOI categorizes fatal injuries into eight sources, as listed in Table 5, with detailed definitions and examples of each source in Appendix A.1.

Among them, "tools, instruments, and equipment" includes non-powered or powered hand tools, ladders, equipment (e.g., protective), and instruments (e.g., surgical); whereas "machinery" includes light and heavy machinery that are capable of motion and are contained in a stationary frame. As industrial robots may be "either fixed in place or mobile for use," robot-related injuries likely fall into either of these categories. While we do not find a significant effect of automation on injuries involving machinery, we do observe a statistically significant increase in fatal injuries related to tools, instruments, and equipment: a 10% increase in automation leads to a 3.5% rise in fatal injuries from tools, instruments, and equipment. Additionally, robot-involved fatalities can be recorded as caused by "vehicles", specifically for example, powered off-road and industrial vehicles, according to Layne (2023).[26] We also find a significant effect from vehicles-induced fatalities: a 10% increase in automation leads to a 1.7% rise in fatal injuries involving vehicles. In Appendix A.2.2, we conduct a fatality analysis by event and find a significant increase of fatalities due to "contact with objects and equipment" and "transportation accidents." These results suggest that the overall increase in fatal workplace injuries may be, at least in part, driven by robot-related physical accidents.

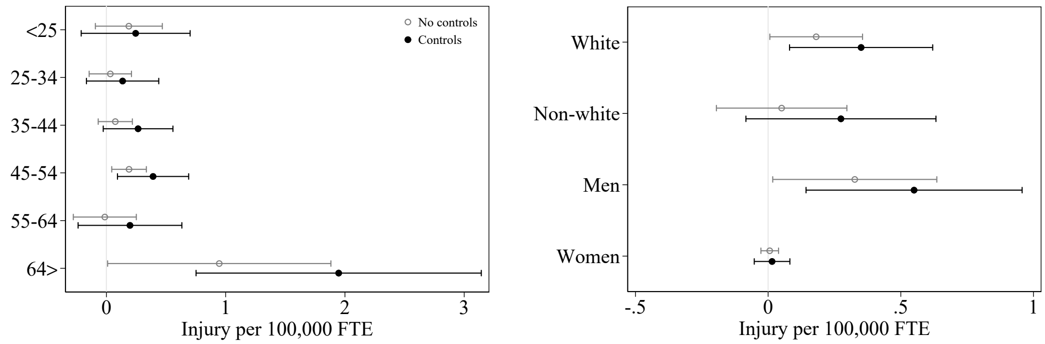
The additional sources include "parts and materials" that corresponds to injuries from machine parts, tool parts, including building materials and nonstructural metal materials; and "chemicals and chemical products" that includes chemicals in various states, e.g., liquid, gases, fumes, that include acids and metallic dusts, powders, and fumes. Robot adoption may impact fatalities from these causes if they insulate workers from working directly with dangerous or hazardous materials. However, we do not find significant effects on fatalities caused by these sources.

We further conduct age-specific analysis to examine potential heterogeneity in effects. Figure 2 presents the effects on fatal injury incidence, with panel (a) displaying results by

[26]Layne (2023) conducted a keyword search (e.g., robot, bionic, autonomous) in incident reports and found that fatalities explicitly recorded as robot-involved are classified under either machinery or vehicles in CFOI. However, as acknowledged in the paper, key words used in the analysis are limited and incomplete, because additional robot-related terms, such as manipulators, effector, and AMR (automous mobile robot), are not included as keywords. This may not only lead to an undercount of fatalities, but also exclude sources of injuries that may be robot-related.

Figure 2: Fatal Workplace Injuries by Worker Demographics

(a) By age group (b) By race and sex



Note: The data is from the 1996-2010 CFOI. This figure presents estimates of the effects of industrial robot exposure on fatal workplace injury rates by demographic groups and 95% confidence intervals. All models include the full set of controls and fixed effects. All regressions are weighted by the state employment of each demographic group. Standard errors are clustered at the state level.

worker age group and panel (b) by race and sex. Each panel includes estimates from a specification without controls and one with a full set of control variables (corresponding to Column (4) in Table 5). The aggregate effect masks substantial heterogeneity across age groups. As shown in Table 1, fatal injury incidence increases with age: workers aged 65 and older experience an average incidence rate of 16.18 per 100,000 full-time equivalent (FTE) workers, compared to 3.37 among those aged 25–34. Older workers are also the most adversely affected by automation, with a 10% increase in robot exposure leading to a 2.2% rise in fatal injury incidence (equivalent to 0.35 additional deaths per 100,000 FTE workers). For middle-aged workers (45–54), robot exposure is associated with a 1.6% increase in fatal injuries, while the effects are not statistically significant for younger workers (under 35) or those aged 55–64. Additionally, as shown in Figure 2(b), white and male workers experience statistically significant increases in fatal injury rates, at 1.3% and 1.2%, respectively. These patterns align with O'Brien et al. (2022), who find that a 10% rise in robot exposure is associated with a 1% increase in mortality from unintentional injuries among men aged 45–54.

The occupational data analyses highlight the multifaceted effects of automation across severity of occupational risks. On one hand, it lowered nonfatal injury incidence, but had adverse effects on fatal injury incidence. Further, the effects differ by worker characteristics: adverse effects from fatal occupational injuries are concentrated among the old, white, and male workers.

4.3 Automation and Hospitalizations

In this section, we supplement findings on occupational injuries with data on hospital discharges. Relative to the occupational injury data, this analysis has several benefits. First, we can measure automation exposure at a more disaggregated CZ level due to the availability of hospital county code data. Second, we can analyze automation's impacts on both physical and mental health conditions using diagnosis codes. Unlike the occupational injury data, however, we are not able to identify whether the hospitalization is work-related. To overcome this limitation, we utilize the primary payer information, which documents whether the primary payer is a private payer (e.g., private HMO), Medicare, Medicaid, or self-pay. Since employer-sponsored health insurance is the primary source of coverage for workers in the US, particularly during our sample period before the enactment of the Affordable Care Act, we provide estimates from using all hospital discharges and discharges with private payer as the primary payer.

In Table 6, we present the estimation results by all payers in columns (1)-(3) and private payers in columns (4)-(6). All results are based on specifications that include cohort$\times$sex cell, hospital, and year fixed effects and demographic controls; and additional controls across specifications are macroeconomic conditions, import penetration, and population size in CZ. In the main text, we focus on physical and mental-health related diagnoses that are more likely to have been impacted by automation, relegating results of other diagnoses (e.g., neoplasm) to Appendix A.2.

First, we note from Table 6, that total admissions decreased among all payers and private payers, but only statistically significantly so among all payers (column (3)). The effects vary largely across diagnoses. Injuries, which include, e.g., fractures, dislocations, sprains and strains of joints, or internal injuries of thorax, decreased significantly with the adoption of robots. The coefficient implies that a 10% increase in robots (from the CZ-level average of 1.49) lowers hospitalizations due to injuries by 2.4%, consistent with our findings from the SOII data. The effect is significant among private payers at 1.9%, implying that these individuals are more likely to have been employed. Another physical injury that may have been prevented from the adoption of robots is backache, for which we do not find a significant effect.

We now consider mental health-related diagnoses. There may be varied effects of automation on mental health. If automation assists workers in their tasks and boosts productivity at workplaces, as evidenced by Graetz and Michaels (2018), it may enhance their mental health. Conversely, if workers fear being replaced by automation (Acemoglu and Restrepo, 2020), they may suffer from higher levels of stress. Therefore, a priori, it is dif-

Table 6: Automation and Hospitalization Discharges by Cause

	All payers			Private payers		
	(1)	(2)	(3)	(4)	(5)	(6)
Total admissions	-0.056*	-0.060*	-0.043	-0.030	-0.036	-0.028
	(0.032)	(0.031)	(0.030)	(0.031)	(0.028)	(0.030)
Injury	-0.169***	-0.167***	-0.160***	-0.131***	-0.131***	-0.126***
	(0.036)	(0.037)	(0.040)	(0.028)	(0.030)	(0.032)
Backache	-0.024	-0.035	-0.031	-0.022	-0.025	-0.024
	(0.036)	(0.034)	(0.034)	(0.030)	(0.030)	(0.029)
Mental disorders	-0.097*	-0.105**	-0.083*	-0.094**	-0.104**	-0.097*
	(0.053)	(0.051)	(0.050)	(0.048)	(0.049)	(0.051)
Despair-related	-0.102	-0.107*	-0.074	-0.093	-0.101	-0.077
	(0.065)	(0.064)	(0.058)	(0.062)	(0.064)	(0.061)
Alcohol abuse	-0.147**	-0.146**	-0.123**	-0.083	-0.085	-0.070
	(0.057)	(0.058)	(0.054)	(0.055)	(0.057)	(0.057)
Substance abuse	-0.107	-0.119*	-0.080	-0.131**	-0.141**	-0.118*
	(0.070)	(0.068)	(0.060)	(0.066)	(0.068)	(0.065)
Opioid abuse	0.030	0.014	0.048	0.085	0.071	0.093
	(0.083)	(0.076)	(0.068)	(0.073)	(0.066)	(0.061)
Suicide attempt	0.011	-0.005	0.023	0.057	0.042	0.061
	(0.070)	(0.066)	(0.060)	(0.061)	(0.054)	(0.050)
Demographics	✓	✓	✓	✓	✓	✓
Macroeconomic controls	✓	✓	✓	✓	✓	✓
Import penetration		✓	✓		✓	✓
(log) Population			✓			✓
CZs	376	376	376	376	376	376
Observations	90,862	90,862	90,862	88,816	88,816	88,816

Note: The data is from the 1996-2010 HCUP NIS. This table presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions. All models include fixed effects for cohort × sex cells, hospitals, and year. All regressions are weighted by the population in cohort × sex cells within CZs. Standard errors clustered at the CZ level are in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ficult to gauge the net effects of automation on mental health. In Table 6, we present automation's impacts on mental disorders, and "despair"-related conditions—alcohol, substance, and opioid abuse, and suicide attempt—combined, and for each category (Case and Deaton, 2017). Our findings suggest that a 10% increase in robots lowers mental disorders and despair-related hospitalizations by 1.2% and 1.1%, respectively, with similar effects in magnitude across all and private payers. It is natural that our estimates for hospitalizations due to mental disorders align qualitatively with those for despair-related hospitalizations, as our definition of mental disorders includes alcohol- and drug-related conditions (e.g., alcohol-induced mental disorders (ICD-9 code 291) and drug dependence (ICD-9 code 304)). Among specific despair-related conditions, we find a larger impact from substance abuse.

In Figure 3, we present results by age groups for each diagnosis in specifications without any controls and with full set of controls.[27] The aggregate results from Table 6 mask a large heterogeneity in how automation impacts workers across different demographics. Figures 3(a) and (b) exhibit pronounced age gradients in physical health benefits of automation. For injuries, hospitalizations decreased with robot adoption for all age groups, with the greatest impact observed among 18-24-year-olds at a 4.8% decrease, and the smallest impact among 55-65-year-olds at 1%.

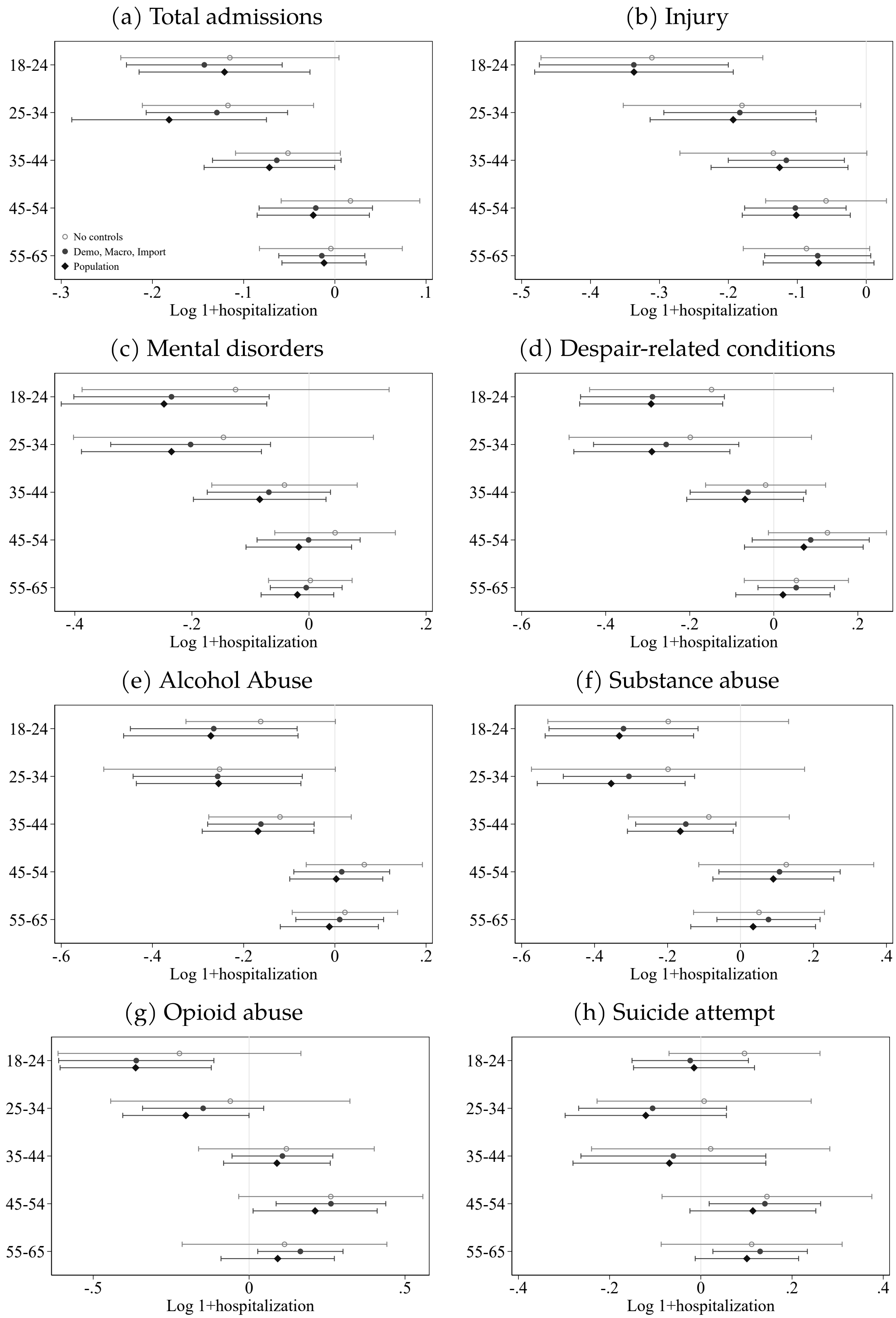
For mental disorders and despair-related conditions, we also find heterogeneous effects across worker ages. In particular, young (18-24) workers are the ones who experience less mental disorders or despair-related conditions, with its effects at 3.6% and 4.3%. In contrast, middle-aged individuals exhibit higher hospitalization rates for despair-related conditions. Opioid abuse hospitalizations increase by 3.2% among those aged 45–54 and by 1.4% among those aged 55–64, while hospitalizations due to suicide attempts rise by 1.7% for individuals aged 45–54 and 1.5% for those aged 55–65. Our findings align with those of O'Brien et al. (2022), who document age-specific heterogeneity in the mortality effects of automation. Specifically, they find that a 10% increase in robot exposure is associated with a 0.9% and 1.8% rise in mortality due to suicide and drug overdose, respectively, among men aged 45–54, relative to 1993. The pattern is also consistent with Albinowski and Lewandowski (2024), who find that automation negatively impacts employment among older workers, as they are less mobile in response to technological shocks. Given Gihleb et al. (2022)'s findings that deteriorating mental health is closely linked to job disruptions, we view our results as evidence that automation-induced job insecurity disproportionately affects the mental health of middle-aged workers.

In Figure 4, we present results by race.[28] We find that automation impacted total admissions and hospitalizations due to injury of non-white workers more significantly as shown in Figure 4(b), with smaller heterogneity across sex. Similar to physical conditions, the automation seemed to have benefited non-whites more than white workers, with no specific

[27]For this analysis, we aggregate the data by age group, sex and hospital and estimate regressions for each age group. Fixed effects for sex, year and hospital are included, along with the control variables described in Section 3.

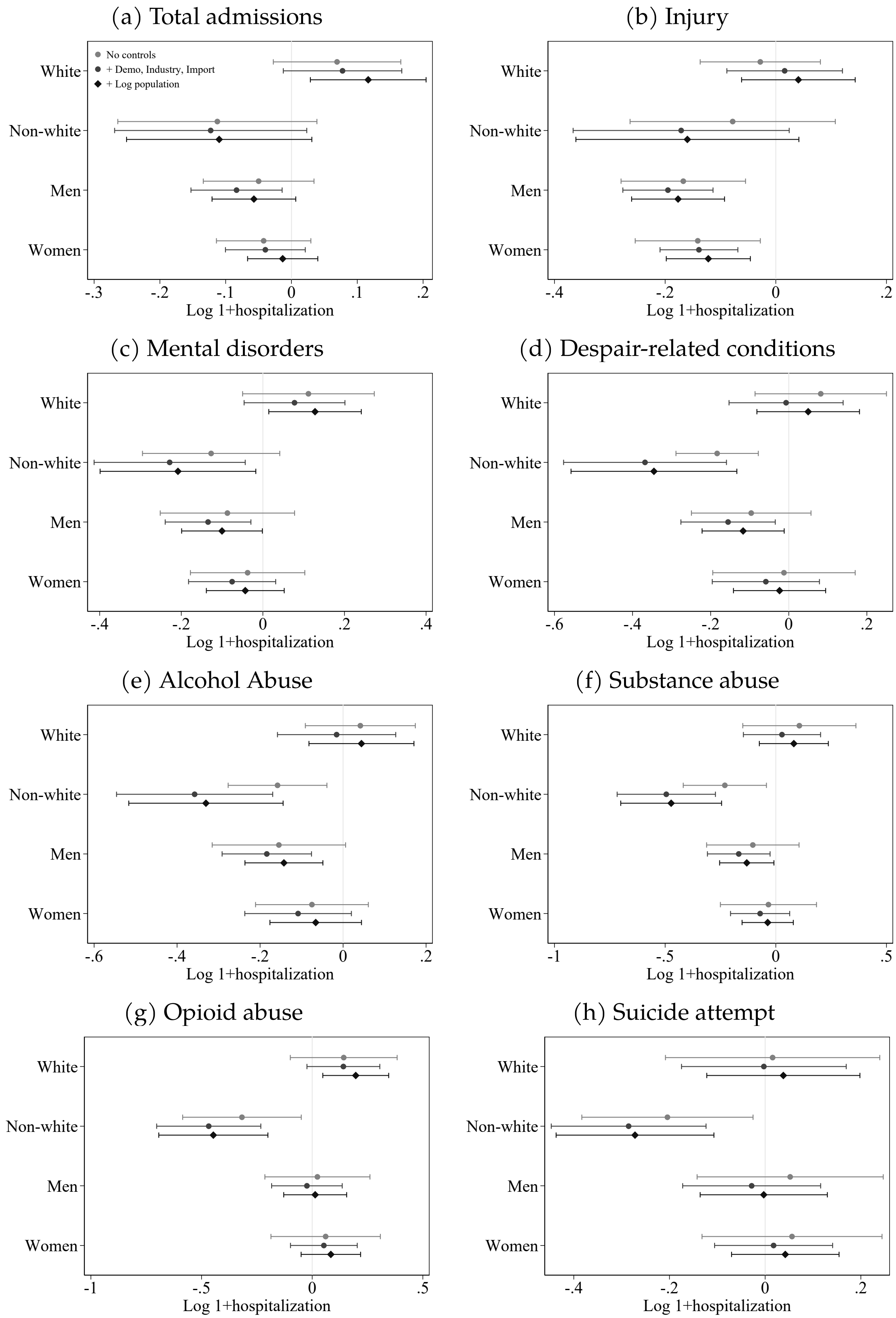
[28]For race analysis, we aggregate the data by cohort, race, and hospital and estimate regressions for each race, controlling for fixed effects for cohort, year, and hospital.

Figure 3: Discharges by Age Group



Note: The data is from the 1996-2010 NIS. This figure presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions for each age group, along with 95% confidence intervals.

Figure 4: Discharges by Race and Sex



Note: The data is from the 1996-2010 NIS. This figure presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions for each race and sex, along with 95% confidence intervals.

differences across sex.

Overall, the hospitalization analyses suggest that automation has widened the disparity in health risks across worker characteristics, especially ages. We see that while young workers in CZs with higher automation exposure experience less hospitalization from injuries, middle-aged workers experienced increased hospitalizations, particularly due to despair-related conditions.

4.4 Robustness Analyses

In this section, we test the robustness of our results across different estimation methods, automation measures, and sample selections.

First, we examine whether our findings hold under a Two-Stage Least Squares (2SLS) estimation. Our baseline analysis employs reduced-form regressions of outcomes on instrumental variables, allowing us to utilize longer observation periods, as US industry-level robot stock data only begins in 2004. To verify the robustness of our results, we perform a 2SLS estimation for the baseline period of 1996-2010, where the US robot exposure, defined in Equation (1), is instrumented by our IV.[29] The results of the 2SLS analysis using a specification with all controls (analogous to column (4) in Tables 4 and 5) are presented in column (1) of Tables 7 and 8.[30] Our findings remain consistent under 2SLS estimation: nonfatal injury rates decrease while fatal injury rates increase with automation. The implied effects of these 2SLS estimates closely align with our baseline results: a 10% increase in robot exposure, as defined in equation (1), from the mean of 0.92 robots per 1,000 workers is associated with a 0.8% decrease in nonfatal injuries and a 1.1% increase in fatal injuries. Similarly, for hospitalization, the 2SLS estimates align with our baseline results in terms of sign and statistical significance.

Next, we validate the robustness of estimates by considering alternative constructions of automation measures. Specifically, we examine three variations in the construction of our instrumental variable as defined in Equation (4). First, we use employment share of all industries instead of manufacturing. In our baseline, we focus on manufacturing industries only, as the IFR data provides more detailed robot stock information for manufacturing industries compared to service industries, allowing for more accurate measurement.

[29]For this exercise, we impute the industry-level US robot stock for 1996–2003 using data from 2004–2010. Specifically, following Acemoglu and Restrepo (2020), we allocate the pre-2004 total US robot stock to each IFR industry proportionally to its share of the classified US stock from 2004–2010. The underlying assumption of this approach is the pattern of industry-level robotization before 2004 was similar to that observed during 2004–2010.

[30]We report the corresponding ordinary least squares estimates in Tables A.10 and A.11 in Appendix A.3.

Table 7: Automation and Workplace Injuries
Alternative Estimation and Automation Measures

	(1) 2SLS	(2) All industry	(3) 1990 shares	(4) EURO9
All nonfatal injuries	-0.421***	-0.267***	-0.721***	-0.189***
	(0.118)	(0.087)	(0.190)	(0.053)
Nonfatal injuries by type				
Injury w/o lost workdays	-0.178**	-0.112*	-0.360***	-0.093**
	(0.087)	(0.060)	(0.132)	(0.034)
Injury w / days of job transfer or restriction	-0.239***	-0.151***	-0.314***	-0.088***
	(0.034)	(0.025)	(0.033)	(0.014)
Injury w / days away from work	-0.037	-0.025	-0.093	-0.019
	(0.043)	(0.028)	(0.063)	(0.015)
All fatal injuries	0.536**	0.330**	0.567***	0.204***
	(0.216)	(0.123)	(0.195)	(0.066)
Fatal injuries by source				
Tools, instruments, and equipment	0.024**	0.015**	0.019	0.009**
	(0.011)	(0.007)	(0.013)	(0.004)
Machinery	0.007	0.005	-0.002	-0.001
	(0.040)	(0.025)	(0.041)	(0.013)
Vehicles	0.314**	0.198**	0.333**	0.118***
	(0.127)	(0.076)	(0.127)	(0.043)
Parts and materials	0.016	0.009	0.001	0.002
	(0.024)	(0.015)	(0.029)	(0.009)
Containers	-0.004	-0.003	-0.011	0.001
	(0.013)	(0.008)	(0.015)	(0.004)
Structures and surfaces	0.040	0.023	0.041	0.015
	(0.044)	(0.026)	(0.042)	(0.016)
Chemicals and chemical products	-0.013	-0.009	-0.014	-0.003
	(0.018)	(0.011)	(0.021)	(0.006)
Persons, plants, animals, and minerals	0.048*	0.029**	0.045*	0.015*
	(0.024)	(0.014)	(0.027)	(0.008)
First-stage F stat.	174.0			
Observations	495	495	495	495
States	33	33	33	33

Note: The data is from the 1996-2010 SOII, CFOI, and HCUP NIS. All models include the full set of controls and fixed effects. All regressions are weighted by the state employment or CZ population . Standard errors clustered at the state or CZ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Automation and Hospitalization Discharges
Alternative Estimation and Automation Measures

	(1) 2SLS	(2) All industry	(3) 1990 shares	(4) EURO9
Total admissions	-0.153	-0.044	-0.088*	-0.025**
	(0.111)	(0.030)	(0.045)	(0.012)
Injury	-0.578***	-0.162***	-0.262***	-0.064***
	(0.160)	(0.040)	(0.060)	(0.020)
Backache	-0.111	-0.034	-0.075	-0.004
	(0.117)	(0.034)	(0.055)	(0.011)
Mental disorders	-0.301	-0.084*	-0.134*	-0.035*
	(0.198)	(0.051)	(0.081)	(0.018)
Despair-related	-0.268	-0.077	-0.154*	-0.024
	(0.220)	(0.058)	(0.089)	(0.024)
Alcohol abuse	-0.442**	-0.125**	-0.248***	-0.035*
	(0.212)	(0.054)	(0.082)	(0.021)
Substance abuse	-0.288	-0.081	-0.148	-0.026
	(0.230)	(0.060)	(0.097)	(0.025)
Opioid abuse	0.173	0.044	0.013	0.014
	(0.244)	(0.069)	(0.112)	(0.034)
Suicide attempt	0.083	0.022	0.041	-0.005
	(0.217)	(0.060)	(0.099)	(0.020)
First-stage F stat.	41.5			
Observations	90862	90862	90862	90862
CZs	376	376	376	376

Note: The data is from the 1996-2010 HCUP NIS. This table presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions. All models include the full set of controls and fixed effects. All regressions are weighted by the population in cohort × sex cells within CZs. Standard errors clustered at the CZ level are in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

It also ensures that the normalized HHI of the shocks is close to zero, one of conditions for satisfying identification conditions of SSIV. Column (2) of Tables 7 and 8 shows that our results remain largely unchanged from the baseline when using the employment share across all industries. Second, we replace the 1970 industry employment shares with the

1990 shares. The baseline uses the 1970 shares to capture the industrial specialization of CZs that predated the onset of automation in the US. Nevertheless, as shown in column (3) of Tables 7 and 8, our results are robust to this alternative IV construction using the 1990 shares. Finally, we test the robustness of our findings by using data from nine European countries, including Germany, Norway, Spain, and the UK, for which the robot stock data is available, in addition to EURO5. While our choice of EURO5 is motivated by the fact that these countries are ahead of the US in robot adoption, allowing us to isolate global technological improvements in robotics, our findings remain robust even when including countries further ahead (Germany) or behind (Norway, Spain, and the UK) in robot adoption. These results are presented in column (4) of Tables 7 and 8.

We conduct the same robustness checks for the heterogeneous effects on fatal workplace injuries and hospitalizations by age group, race, and sex. The results, presented in Tables A.7, A.8, and A.9, are based on 2SLS estimation and alternative IV constructions. These results confirm that the heterogeneity observed in the baseline persists: increased fatal injuries among individuals aged 45–54, 65 and older, white workers, and men; and decreased hospitalizations due to injuries, mental disorders, and despair-related conditions among younger age groups.

Lastly, we further demonstrate the robustness of our findings regarding sample choices, with detailed results presented in Tables A.12–A.14, and Figure A.3 in Appendix A.3. While in CFOI, data on fatal injury is available for all states and DC, in SOII, nonfatal injury data is available for 43 states and some states are missing in some years. In our baseline, we restrict the sample of SOII and CFOI analyses to a balanced panel of 33 states for consistency. In Tables A.12 and A.13, we report results using all states available and find robust effects. Additionally, to ensure that our results are not driven by any single state, we conduct a leave-one-out analysis for the workplace injury regressions by excluding one state at a time and re-estimating Equation (2). As shown in Figure A.3, the estimates remain consistent across the excluded states, with Michigan being the only exception. Although the estimates excluding Michigan differ slightly, they still exhibit qualitatively consistent patterns. In particular, the impact of automation on nonfatal injuries resulting in days away from work declines more steeply, while the effect on fatal injury incidence rises significantly. The hospitalization results also remain robust to excluding CZs with the highest or lowest (or both) robot exposure as shown in Table A.14.

5 Discussion

5.1 Quantifying the Occupational Injury Effects of Automation

Our occupational injury analyses suggest that automation has led to a divergence in the severity of injuries at workplaces. While robot adoption has contributed to a decline in nonfatal injuries, it has simultaneously increased the incidence of more severe, fatal injuries. We use these estimates to conduct a back-of-the-envelope calculation to assess the economic implications of these effects.

In our baseline sample states, robot exposure, as defined in Equation (4), increased from 0.96 to 2.31 robots per 1,000 manufacturing workers between 1996 and 2010. Our estimates indicate that automation reduced nonfatal workplace injuries by 0.35 per 100 workers over this period. Given the employment of 141.4 million in 1996, this translates to an estimated reduction of 498,149 nonfatal injuries, or 33,209 fewer injuries annually. Additionally, we estimate a decrease of 6,953 injury-related hospitalizations per year, based on an increase of 1.15 in CZ-level robot exposure and the 1996 baseline of 620,577 injury-related hospitalizations. This is consistent with our estimate of nonfatal workplace injury reduction, considering that nonfatal injuries involving days away from work account for approximately 30% of total nonfatal injuries (see Table 1), and not all such injuries would result in hospitalization. At the same time, our findings suggest that automation increased workplace fatalities by 634 between 1996 and 2010, or 42 per year.[31]

To estimate the cost savings and burdens associated with automation's impact on injuries, we use the estimated cost of occupational injuries from Leigh (2011), the value of a statistical injury (VSI), and the value of a statistical life (VSL).[32] According to Leigh (2011), the average cost of a nonfatal occupational injury—including medical expenses and indirect costs such as hiring and training replacements—is \$32,900 (in 2023 USD). Based on this estimate, the reduction in nonfatal injuries due to automation results in approximately \$1.1 billion in annual cost savings. If we use the VSI estimate, which reflects the willigness to pay to reduce risks of nonfatal injuries, of \$57,400 (in 2023 USD) from Garen (1988), the reduction in nonfatal injuries due to automation translates to approximately \$1.9 billion in annual cost savings.[33] In contrast, the additional costs associated

[31]This estimate is based on all workplace fatalities. We find 28 additional fatalities (2 per year) attributed to "tools, instruments, and equipment" and 372 additional fatalities (25 per year) related to "vehicles" between 1996 and 2010.

[32]Leigh (2011) calculate the estimates based on empirical data such as injury reports, healthcare expenditures, and labor markt records. On the other hand, VSI and VSL are derived from labor market equilibrium in hedonic wage models, capturing the trade-off between wages and risk (nonfatal for VSI and fatal for VSL).

[33]While we account for all nonfatal injuries in this calculation, most VSI studies focus on injuries involving

with increased fatal injuries range from $262 million to $516 million per year, based on the 25th and 75th percentile VSL estimates of $6.2 million and $12.3 million from Banzhaf (2022).[34] This implies that the economic burden of rising fatal injuries offsets 14% to 27% of the cost savings from reduced nonfatal injuries using VSI; or 24% to 47%, using Leigh (2011)'s estimates.[35] It is important to note, however, that this quantification primarily captures the effects of injuries occurring in workplaces and does not necessarily account for the costs (or benefits) associated with mental health conditions.

5.2 Implications for Policy

Our findings have implications for policies aimed at preventing workplace injuries and providing insurance to those affected.

First and foremost, the rise in fatal injuries underscores the need for enhanced safety training in workplaces. In the US, the Occupational Safety and Health Administration (OSHA) establishes standards that require employers to train employees on workplace safety. These training requirements include programs to prevent injury and illness, for example, in performing welding, cutting, and brazing, or operating machinery. In 2025, employers found in violation face penalties of up to $16,550 per violation, or $165,514 per violation if deemed willful or repeated.[36] Given the negative impact of automation-related fatalities, strengthening safety training requirements to reflect emerging technologies and tightening enforcement mechanisms may be necessary to reinforce the importance of preventive measures.

On the worker-side, social insurance policies have important roles for those impacted by automation. Among them, workers' compensation program, a state-run program, plays an important role in the US, providing insurance coverage to individuals who are injured or become ill while working. It covers millions of workers annually: In 2020, nearly 136 million jobs were covered, with total covered wages amounting to $8.7 trillion (Murphy and Wolf, 2022).[37] The program covers four main areas: medical care, temporary dis-

days away from work, with Garen (1988) being an exception. Despite being dated, Garen (1988)'s estimate seems reasonable given a recent VSI estimate of $132,700 from Viscusi and Gentry (2015), which focuses on injuries with days away from work.

[34] For inflation and income adjustments to VSI and VSL, we follow the methodology outlined in Banzhaf (2022) and its supplementary appendix, applying a rule-of-thumb income elasticity of 1.

[35] We obtain a similar cost-savings estimate when using 2SLS and the US robot measure, which imply an annual decrease of 31,744 nonfatal injuries and an increase of 606 fatal injuries.

[36] See `https://www.osha.gov/penalties` for details.

[37] Industries such as underground mining, construction, and transportation incur some of the highest workers' compensation costs per employee per hour due to the hazardous nature of their work, according to `https://workcomplab.com/insurance-industry/`.

ability, permanent disability, and death benefits.[38] Medical expenses are fully covered, but wage replacement only kicks in if time lost exceeds the three-to-seven-day waiting period. Temporary and permanent disability benefits include wage replacement and are given to workers depending on their ability to return to their regular jobs. In cases of workplace fatalities, death benefits cover funeral costs and provide financial support to dependents. While mental health conditions are only covered in 34 states, its coverage varies.[39]

We find that robot exposure has led to a significant reduction in nonfatal workplace injuries, particularly those requiring job transfers and restricted duties. This may suggest that automation is supporting workers in physically demanding or repetitive tasks that previously resulted in injuries requiring time away from work, potentially lowering claims for temporary disability benefits. Given that temporary benefit payments make up a large share of workers' compensation costs, a continued shift toward automation could lead to long-term cost reductions in the system. However, the new risks introduced by automation that lead to increased mental conditions (for middle-aged workers) and higher fatalities may require adjustments to workers' compensation policies, particularly regarding coverage for robot-related mental health conditions and workplace deaths.

6 Conclusion

This paper examines the impact of automation on workers' health risks. Because automation impacts workers through several channels—such as reducing physical burden at work, increasing productivity at the firm level, or displacing workers—its health effects may vary, and could differ based on worker characteristics. We conduct a comprehensive analysis on this issue, by analyzing data on nonfatal and fatal workplace injuries, as well as hospitalization discharge records with medical diagnoses. We highlight two key findings. First, while automation has led to a decline in nonfatal occupational injuries, it has simultaneously increased fatal occupational injuries, impacting the severity of workplace health risks. This discrepancy in automation's effects across injury severity may arise from automation's role in assisting workers with dangerous tasks while simultaneously introducing new risks that require worker adaptation. Second, while automation decreased hospitalizations among young workers for injuries and conditions related to mental and despair-related conditions, it had an adverse effect on middle-aged and older workers, suggesting that health risks have become more varied across different age groups. Such effects may stem from younger workers adapting more easily to new technology and align

[38]See `https://www.nasi.org/learn/workers-compensation-disability`.
[39]See `https://www.ncsl.org/labor-and-employment/`.

with pevious research documenting greater displacement effects on older workers due to automation. Overall, despite the contrasting effects on nonfatal and fatal injuries, the net economic impact of automation on worker safety remains positive.

Our study highlights the need for robust worker safety training and comprehensive social insurance policies that support workers facing a range of physical and mental health challenges. Furthermore, it is crucial to examine how differential technology adoption across industries and occupations affect workers' health risks.

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Appendix

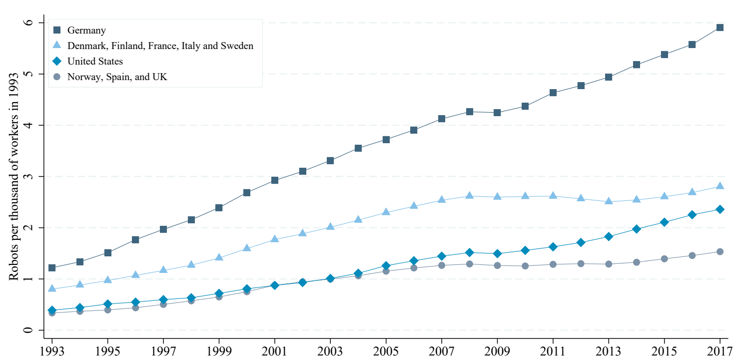
A.1 Additional Data Details

A.1.1 Automation in the US and EURO5

Figure A.1 shows the trend of robot stocks for European countries and the US. We use the robot exposure based on EURO5 (Denmark, Finland, France, Italy, and Sweden) in the baseline IV construction to capture variation driven by global technological advances. We exclude Germany because its robot adoption is far ahead of that of the US, which may make it less relevant. Meanwhile, other European countries (Norway, Spain, and the UK) are not included as their robot adoption lags behind that of the US.

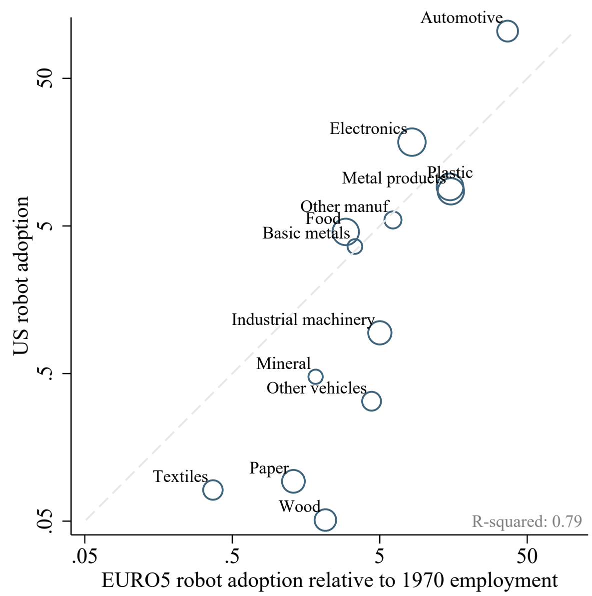
To examine the correlation between US and EURO5 robot adoption at the industry level, in Figure A.2, we plot the average of industry-level robot stock per 1,000 workers in the US, $\left(\frac{M_{it}^{\text{US}}}{L_{it}^{\text{US}}}\right)$ in 2004-2010 and in EURO5 $\left(\frac{1}{5}\sum_{j\in\text{EURO5}}\frac{M_{it}^{j}}{L_{i,1970}^{j}}\right)$ in 1996-2010. There is a close association between the two measures with an R-squared of 0.8, mitigating concerns about a weak IV.

Figure A.1: Robot adoption in the United States and Europe



Note: The robot measure is constructed using data from IFR, CBP, and EU KLEMS. The figure displays the robot stock per 1,000 workers in the US and Europe from 1993 to 2017.

Figure A.2: Robot adoption in the United States and EURO5 by industry



Note: Robot measures are constructed using data from IFR, CBP, and EU KLEMS. The figure displays the average industry-level robot stock per 1,000 workers in the U.S. (2004–2010) and EURO5 (1996–2010), where the EURO5 measure is based on robot stock per 1,000 workers in 1970 (as in Equation 4). The dashed line indicates the 45-degree line. The circle size represents the 1996-2010 average US employment in the industry.

A.1.2 CFOI: Source of Injury

Table A.1 presents the categorization of injury sources in CFOI from the Occupational Injury and Illness Classification Manual (BLS, 1992).

Table A.1: Description of Source of Injuries (CFOI)

Source of injury	Description and example
Chemicals and Chemical Products	This division includes chemicals and chemical products in various states—liquids, gases, fumes, vapors, and solids. Includes: acids; alkalies; aromatics and hydrocarbon derivatives; halogens and their compounds; metallic dusts, powders and fumes; agricultural chemicals and pesticides; coal, natural gas, petroleum fuels and products; other chemicals and chemical products
Containers	This division classifies receptacles that are commonly used to hold, store, or carry materials. All containers may be empty or full. Pressurized and nonpressurized containers are fix-shaped receptacles used to hold,store, or carry materials. Variable restraint containers include bundles, packages, and rolls where thematerial being contained is usually the surface of the container. Includes: Pressurized containers; nonpressurized containers; variable restraint containers; dishes, cups, glasses; luggage; skids and pallets.
Machinery	This division classifies light and heavy machinery which perform specific functions or processes under power. Machinery is defined as a combination of smaller machines (elements or parts) which are capable of motion and are contained in a stationary frame. Includes: agricultural and garden machinery; construction, logging, and mining machinery; heating, cooling, and cleaning machinery and appliances; material and personnel handling machinery (e.g., conveyors, cranes, hoists, elevators, etc.); metal, woodworking, and special material machinery; office and business machinery; special process machinery; miscellaneous machinery
Parts and Materials	This division classifies machine parts, tool parts, and automobile parts, as well as building materials, insulating materials, and nonstructural metal materials.

Table A.1 – continued from previous page

Source of injury	Description and example
	Includes: building materials—solid elements; structural metal materials; fasteners, connectors, ropes, ties; hoisting accessories; machine, tool, and electric parts; metal materials—nonstructural; tars, sealants, caulking, insulating material; tarps and sheeting—nonmetal; vehicle and mobile equipment parts
Persons, Plants, Animals, and Minerals	This division classifies living organisms (including infectious and parasitic agents) and their products, as well as raw, metallic and nonmetallic minerals. Includes: animals and animal products; fresh or processed food products; infectious and parasitic agents; metallic minerals; nonmetallic minerals (except fuel); person—injured or ill worker; person—other than injured or ill worker; bodily fluids; unprocessed plants, trees, vegetation
Structures and Surfaces	This division classifies all types of structures and structural elements including building structures and systems, bridges, stadia, tunnels, towers, and dams as well as other structural elements. Includes: building systems; floors, walkways, ground surfaces; other structural elements; structures
Tools, Instruments, and Equipment	This division classifies handtools (nonpowered; powered; power not determined), ladders (fixed; movable), equipment (photographic; protective; recreation, athletic), and instruments (medical and surgical) Includes: nonpowered handtools; powered handtools; handtools—power not determined; ladders; medical and surgical instruments and equipment; photographic equipment; protective equipment (except clothing); recreation and athletic equipment; clocks; cooking and eating utensils (except knives); firearms and other weapons; musical instruments; sewing notions, n.e.c.; writing, drawing, and art supplies
Vehicles	This division classifies vehicles that generally move on wheels, runners, water, or air. Includes: air vehicles; rail vehicles and rail cars; water vehicles; motorized highway vehicles; nonmotorized highway vehicles; off-road vehicles including powered plant and industrial vehicles; tractors; nonpowered plant and industrial vehicles

A.1.3 NIS: Diagnosis Definitions and Summary Statistics

Table A.2 details the mapping between diagnosis conditions and ICD-9 codes following Adda and Fawaz (2020); and Table A.3, summary statistics of hospitalization by diagnoses (analogous to Table 2) omitted from the main text.

Table A.2: Diagnosis Definitions

Conditions	ICD-9 codes
Injury	800–869
Backache	724.0/724.99
Mental disorders	290–311
Alcohol abuse	305, 291–292, 303, 571.0-571.4, E860.0
Substance abuse	304, 292.0, 305.2/305.95, E850.0, E850.1, 970.8
Opioid abuse	304.00, 304.01, 304.02, 304.03, 304.70, 304.71, 304.72, 304.73, 305.50, 305.51, 305.52, 305.53, 965.00, 965.09, E850.2, E935.2
Suicide attempt	E850–E859, E868.2, E950–E960
Homicides and crime	E960–E979
Heart problems	410–438
Infectious diseases	001–139
Respiratory diseases	460–519
Endocrine, nutritional and metabolic diseases	240–280
Inappropriate diet	V69.1
Neoplasm (all)	140–239
Neoplasm (tobacco related)	162, 140–151, 153–154, 157, 160–161, 179–180, 183, 188–189, 205

Table A.3: Summary Statistics of Hospital Discharges for Other Diagnoses (per Hospital)

	Mean	SD	P25	P50	P75
Homicides and crime	105.7	334.9	0.0	15.8	61.3
Heart problems	4,177.8	5,851.4	443.6	1,983.6	5,505.3
Infectious diseases	2,127.0	3,173.0	253.2	1,000.4	2,682.9
Respiratory diseases	3,938.5	5,147.1	577.0	2,161.7	5,261.4
Digestive system	4,642.2	6,151.5	685.0	2,563.8	6,107.7
Endocrine nutritional metabolic	7,302.0	10,043.4	900.5	3,656.2	9,718.9
Diet related	6,101.5	8,559.5	709.8	2,964.6	8,122.1
Neoplasm all	1,979.6	3,447.4	162.4	772.8	2,400.4
Neoplasm tobacco related	542.9	992.9	41.1	200.9	633.5
Observations			9,950		

Note: The data is from the NIS for years 1996-2010.

A.2 Additional Empirical Results

A.2.1 States and Commuting Zone Characteristics

Table A.4 summarizes the state and CZ-level characteristics in 1996, the start of our sample period, both for all and in-sample data. At the state-level, there are no significant differences in observed characteristics in our sample compared to those in all states. The average automation exposure in the commuting zones within our sample is lower because Michigan, the state with the highest robot exposure, is not included (the robustness analyses in Appendix A.3 confirm that our results hold in the full sample). However, it is not statistically different from the overall average automation exposure across all commuting zones.

Table A.4: State and CZ Characteristics in 1996

	States		Commuting Zones	
	All	In sample	All	In sample
Robot exposure	0.95	0.96	0.93	0.83
	(0.63)	(0.69)	(0.70)	(0.41)
Share of age 25-34	0.15	0.15	0.15	0.15
	(0.01)	(0.01)	(0.02)	(0.02)
Share of age 35-44	0.16	0.16	0.16	0.16
	(0.01)	(0.01)	(0.01)	(0.01)
Share of age 45-54	0.12	0.12	0.12	0.12
	(0.01)	(0.01)	(0.01)	(0.01)
Share of age 55-64	0.08	0.08	0.08	0.08
	(0.01)	(0.01)	(0.01)	(0.01)
Share of age 65+	0.12	0.11	0.13	0.13
	(0.02)	(0.01)	(0.03)	(0.03)
Share of white	0.83	0.82	0.73	0.74
	(0.09)	(0.09)	(0.17)	(0.16)
Share of non-hispanic black	0.13	0.13	0.12	0.11
	(0.09)	(0.08)	(0.10)	(0.09)
Share of high school or less	0.76	0.76	0.76	0.75
	(0.04)	(0.04)	(0.07)	(0.07)
Share of manufacturing	0.16	0.16	0.16	0.15
	(0.05)	(0.05)	(0.08)	(0.07)
Share of light manufacturing	0.03	0.03	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Import penetration	0.85	0.88	0.86	0.85
	(0.28)	(0.29)	(0.59)	(0.57)
Unemployment rate	0.05	0.06	0.05	0.06
	(0.01)	(0.01)	(0.02)	(0.02)
Observations	51	33	738	387

Note: Statistics are weighted by the 1996 population, and standard deviations are in parentheses.

A.2.2 Fatal Workplace Injuries by Event

Table A.5 reports estimates of the impact of automation on fatal injury rates by event. In our preferred specification in column (4), we find that automation is associated with increases in fatal injuries caused by contact with objects and equipment, exposure to harmful substances, and transportation accidents, similar to findings in Layne (2023).

Table A.5: Automation and Fatal Workplace Injuries by Event (per 100,000 FTE Workers)

	(1)	(2)	(3)	(4)	Mean
Panel A: Total fatal injury (per 100,000 FTE)					
All fatal injuries	0.177*	0.136	0.295**	0.332**	4.354***
	(0.089)	(0.097)	(0.130)	(0.123)	
Fatal injuries by event					
Contact with objects and equipment	0.014	0.012	0.027	0.040*	0.729
	(0.018)	(0.018)	(0.029)	(0.023)	
Falls	0.008	0.006	0.021	0.023	0.550
	(0.011)	(0.013)	(0.024)	(0.025)	
Exposure to harmful substances	0.015**	0.016	0.028*	0.028*	0.365
	(0.006)	(0.010)	(0.014)	(0.015)	
Transportation accidents	0.116**	0.090	0.168**	0.182**	1.852
	(0.053)	(0.063)	(0.069)	(0.073)	
Fires and explosions	-0.021*	-0.019*	-0.017	-0.012	0.120
	(0.011)	(0.009)	(0.015)	(0.014)	
Assaults and violent acts	0.039	0.024	0.059	0.063	0.684
	(0.024)	(0.029)	(0.048)	(0.048)	
Other events or exposures	0.001	0.001	0.001	0.001	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	
Demographics		✓	✓	✓	
Industry shares			✓	✓	
Import penetration				✓	
Observations	495	495	495	495	495
States	33	33	33	33	

Note: The data is from the 1996-2010 CFOI. This table presents estimates of the effects of industrial robot exposure on fatal injury incidence per 100,000 FTE workers. All regressions are weighted by state employment. Standard errors clustered at the state level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2.3 Hospitalization Discharges by Diagnoses

Table A.6 reports the effects of automation on discharges by specific diagnoses, not reported in the main text. We find a significant decrease in discharges due to tobacco-related neoplasm, but not from other causes, e.g., homicide or respiratory diseases.

Table A.6: Automation and Hospitalization: Discharges by Cause

	All payers			Private payers		
	(1)	(2)	(3)	(4)	(5)	(6)
Homicides and crime	0.022	0.010	0.044	0.016	0.006	0.031
	(0.074)	(0.068)	(0.069)	(0.051)	(0.044)	(0.050)
Heart problems	-0.016	-0.021	0.001	-0.032	-0.037	-0.024
	(0.035)	(0.034)	(0.033)	(0.031)	(0.031)	(0.031)
Infectious diseases	0.030	0.024	0.054	0.045	0.035	0.057
	(0.045)	(0.043)	(0.041)	(0.041)	(0.038)	(0.040)
Respiratory diseases	0.023	0.019	0.038	0.035	0.027	0.036
	(0.037)	(0.036)	(0.033)	(0.036)	(0.034)	(0.037)
Digestive system	-0.026	-0.034	-0.013	-0.009	-0.019	-0.004
	(0.040)	(0.039)	(0.038)	(0.042)	(0.037)	(0.043)
Endocrine nutritional metabolic	-0.019	-0.021	-0.003	0.009	0.006	0.016
	(0.031)	(0.031)	(0.030)	(0.036)	(0.035)	(0.038)
Diet related	-0.026	-0.031	-0.009	-0.010	-0.016	-0.002
	(0.034)	(0.032)	(0.032)	(0.031)	(0.029)	(0.032)
Neoplasm all	-0.057	-0.065	-0.043	-0.015	-0.024	-0.004
	(0.046)	(0.045)	(0.044)	(0.050)	(0.045)	(0.049)
Neoplasm tobacco related	-0.100***	-0.106***	-0.083**	-0.032	-0.041	-0.017
	(0.034)	(0.037)	(0.033)	(0.040)	(0.037)	(0.040)
Death	-0.016	-0.009	0.008	-0.027	-0.023	-0.008
	(0.039)	(0.038)	(0.038)	(0.036)	(0.037)	(0.035)
Demographics	✓	✓	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓	✓	✓
Import penetration		✓	✓		✓	✓
Log population			✓			✓
Observations	90,862	90,862	90,862	88,816	88,816	88,816
CZs	376	376	376	376	376	376

Note: The data is from the 1996-2010 HCUP NIS. This table presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions. All models include fixed effects for cohort $\times$ sex cells, hospitals, and year. All regressions are weighted by the population in cohort $\times$ sex cells within CZs. Standard errors clustered at the CZ level are in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.3 Robustness Checks

A.3.1 Alternative Estimation and Automation Measures

In this section, we present tables and figures that support the robustness of our findings. Tables A.7, A.8, and A.9 confirm that the magnitude and statistical significance of our heterogeneity estimates remain consistent under an alternative estimation method and alternative robot exposure measures, as detailed in the robustness checks in the main text (Tables 7 and 8). Specifically, Table A.7 corresponds to Figure 2, where we examine the heterogeneous effects of industrial robot exposure on fatal injuries by age group, race, and sex. Similarly, Tables A.8 and A.9 demonstrate the robustness of the heterogeneous effects of robot exposure on hospitalizations across age groups (Figure 3) and by race and sex (Figure 4). For ease of comparison, we report the baseline reduced-form estimates in column (1) of Tables A.7, A.8, and A.9. In column (2), we present 2SLS estimates. Next, we test the robustness of reduced-form estimates under alternative constructions of the robot exposure measure: using employment shares of all industries instead of manufacturing industries (column (3)); replacing 1970 employment shares with 1990 shares (column (4)); and incorporating robot adoption data from nine European countries instead of EURO5 (column (5)). Lastly, we report estimates from OLS regressions in Tables A.10 and A.11.

Table A.7: Fatal Workplace Injuries by Worker Demographics
Alternative Estimation and Automation Measures

	(1) Baseline	(2) 2SLS	(3) All industry	(4) 1990 shares	(5) EURO9
By age group					
<25	0.245	0.397	0.242	0.414	0.152
	(0.224)	(0.374)	(0.224)	(0.391)	(0.130)
25-34	0.136	0.220	0.132	0.215	0.096
	(0.149)	(0.247)	(0.147)	(0.242)	(0.082)
35-44	0.266*	0.433*	0.263*	0.367	0.128*
	(0.143)	(0.252)	(0.143)	(0.230)	(0.069)
45-54	0.391**	0.631**	0.398**	0.753***	0.226***
	(0.147)	(0.244)	(0.148)	(0.259)	(0.081)
55-64	0.198	0.312	0.191	0.036	0.132
	(0.214)	(0.344)	(0.214)	(0.391)	(0.103)
65+	1.948***	3.077***	1.876***	2.418*	1.025***
	(0.587)	(1.036)	(0.580)	(1.213)	(0.337)
By race and sex					
White	0.350**	0.574**	0.348**	0.626**	0.242***
	(0.132)	(0.230)	(0.132)	(0.229)	(0.079)
Non-white	0.274	0.431	0.279	0.480	0.103
	(0.176)	(0.297)	(0.178)	(0.285)	(0.080)
Men	0.550***	0.889**	0.550***	0.966***	0.331***
	(0.200)	(0.349)	(0.201)	(0.330)	(0.104)
Women	0.015	0.024	0.013	0.001	0.020
	(0.033)	(0.054)	(0.033)	(0.052)	(0.021)
First-stage F stat.		171.8			
Observations	495	495	495	495	495
States	33	33	33	33	33

Note: The data is from the 1996-2010 CFOI. This table presents estimates of the effects of industrial robot exposure on fatal workplace injury rates by demographic groups. All models include the full set of controls and fixed effects. All regressions are weighted by the state employment of each demographic group. Standard errors are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Hospitalization Discharges by Age Group
Alternative Estimation and Automation Measures

		(1) Baseline	(2) 2SLS	(3) All industry	(4) 1990 shares	(5) EURO9
Total admissions	18-24	-0.065	-0.238	-0.068	-0.120	-0.048**
		(0.054)	(0.202)	(0.054)	(0.083)	(0.021)
	25-34	-0.066*	-0.235	-0.066*	-0.086	-0.034**
		(0.038)	(0.154)	(0.038)	(0.057)	(0.015)
	35-44	-0.032	-0.115	-0.034	-0.073	-0.018
		(0.035)	(0.129)	(0.035)	(0.052)	(0.013)
	45-54	0.003	0.012	0.002	-0.014	-0.008
		(0.031)	(0.113)	(0.031)	(0.048)	(0.013)
	55-65	-0.001	-0.004	-0.002	-0.002	-0.011
		(0.027)	(0.097)	(0.027)	(0.044)	(0.012)
Injury	18-24	-0.326***	-1.194***	-0.330***	-0.488***	-0.124***
		(0.092)	(0.392)	(0.093)	(0.133)	(0.038)
	25-34	-0.231***	-0.827***	-0.232***	-0.363***	-0.100***
		(0.071)	(0.277)	(0.072)	(0.106)	(0.033)
	35-44	-0.092*	-0.331**	-0.093*	-0.168**	-0.048**
		(0.047)	(0.161)	(0.047)	(0.073)	(0.024)
	45-54	-0.076	-0.276	-0.078	-0.135*	-0.029
		(0.048)	(0.168)	(0.048)	(0.079)	(0.020)
	55-65	-0.072	-0.261	-0.072	-0.118	-0.046
		(0.048)	(0.178)	(0.048)	(0.073)	(0.029)
Mental disorders	18-24	-0.158*	-0.578	-0.159*	-0.243	-0.074**
		(0.092)	(0.365)	(0.093)	(0.150)	(0.031)
	25-34	-0.129**	-0.462*	-0.127*	-0.125	-0.052**
		(0.064)	(0.274)	(0.064)	(0.106)	(0.025)
	35-44	-0.023	-0.082	-0.022	-0.014	-0.016
		(0.053)	(0.197)	(0.054)	(0.083)	(0.019)
	45-54	0.042	0.152	0.040	0.045	0.012
		(0.045)	(0.165)	(0.046)	(0.072)	(0.015)
	55-65	0.016	0.059	0.015	0.001	-0.003
		(0.032)	(0.116)	(0.032)	(0.055)	(0.015)
Despair-related	18-24	-0.258**	-0.945**	-0.262***	-0.452***	-0.106***
		(0.101)	(0.435)	(0.101)	(0.160)	(0.038)
	25-34	-0.204***	-0.731**	-0.203***	-0.326**	-0.072**
		(0.078)	(0.350)	(0.078)	(0.128)	(0.030)
	35-44	-0.034	-0.122	-0.036	-0.071	-0.017
		(0.061)	(0.221)	(0.061)	(0.095)	(0.027)
	45-54	0.114*	0.410*	0.110*	0.151	0.048*
		(0.065)	(0.245)	(0.065)	(0.098)	(0.026)
	55-65	0.037	0.134	0.034	-0.012	0.015
		(0.045)	(0.169)	(0.045)	(0.076)	(0.017)

Note: The data is from the 1996-2010 HCUP NIS. This table presents estimates of the effects of robot exposure on log of 1 plus hospitalizations with specific conditions by age group. All models include the full set of controls, and are weighted by the population in cohort×sex cells within CZs. Standard errors in parentheses are clustered at the CZ level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Discharges by Race and Sex
Alternative Estimation and Automation Measures

		(1) Baseline	(2) 2SLS	(3) All industry	(4) 1990 shares	(5) EURO9
Total admissions	White	0.117***	0.396**	0.116**	0.148*	0.027
		(0.045)	(0.199)	(0.045)	(0.079)	(0.022)
	Non-white	-0.110	-0.408	-0.114	-0.206*	-0.058*
		(0.072)	(0.279)	(0.071)	(0.121)	(0.031)
	Men	-0.057*	-0.215*	-0.059*	-0.128**	-0.030**
		(0.032)	(0.125)	(0.032)	(0.051)	(0.013)
	Women	-0.013	-0.050	-0.015	-0.035	-0.016
		(0.027)	(0.103)	(0.027)	(0.041)	(0.011)
Injury	White	0.041	0.139	0.040	0.039	0.004
		(0.052)	(0.187)	(0.053)	(0.087)	(0.027)
	Non-white	-0.160	-0.593*	-0.166	-0.341*	-0.068
		(0.102)	(0.333)	(0.103)	(0.185)	(0.045)
	Men	-0.177***	-0.664***	-0.179***	-0.314***	-0.070***
		(0.043)	(0.176)	(0.043)	(0.064)	(0.021)
	Women	-0.122***	-0.459***	-0.123***	-0.186***	-0.050**
		(0.039)	(0.146)	(0.039)	(0.062)	(0.020)
Mental disorders	White	0.128**	0.434**	0.128**	0.176*	0.035
		(0.058)	(0.219)	(0.058)	(0.101)	(0.027)
	Non-white	-0.208**	-0.772*	-0.210**	-0.335*	-0.077*
		(0.097)	(0.461)	(0.096)	(0.175)	(0.040)
	Men	-0.100**	-0.377*	-0.102**	-0.181**	-0.040**
		(0.050)	(0.206)	(0.051)	(0.083)	(0.018)
	Women	-0.043	-0.162	-0.043	-0.064	-0.022
		(0.049)	(0.191)	(0.049)	(0.079)	(0.018)
Despair-related	White	0.050	0.169	0.046	0.001	0.012
		(0.067)	(0.229)	(0.067)	(0.114)	(0.027)
	Non-white	-0.345***	-1.281**	-0.349***	-0.584***	-0.116***
		(0.108)	(0.570)	(0.107)	(0.202)	(0.042)
	Men	-0.117**	-0.439**	-0.121**	-0.243***	-0.036
		(0.053)	(0.223)	(0.053)	(0.084)	(0.023)
	Women	-0.024	-0.089	-0.024	-0.062	-0.011
		(0.060)	(0.231)	(0.061)	(0.094)	(0.026)

Note: The data is from the 1996-2010 HCUP NIS. This table presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions for each race and sex. All models include the full set of controls and fixed effects. All regressions are weighted by the population in cohort $\times$ sex cells within CZs. Standard errors clustered at the CZ level are in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Automation and Workplace Injuries
OLS Estimation

	(1)	(2)	(3)	(4)
All nonfatal injuries	-0.572***	-0.498***	-0.433***	-0.613***
	(0.104)	(0.119)	(0.108)	(0.139)
All fatal injuries	0.092	0.010	0.001	0.063
	(0.141)	(0.138)	(0.137)	(0.144)
Demographics		✓	✓	✓
Industry shares			✓	✓
Import penetration				✓
Observations	759	759	759	561
States	33	33	33	33

Note: The data is from the 1996-2010 SOII and CFOI. This table presents OLS estimates of the effects of industrial robot exposure on nonfatal injury incidence per 100 FTE workers and on fatal injury incidence per 100,000 FTE workers. All regressions are weighted by the state employment. Standard errors are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Automation and Hospitalization Discharges by Cause
OLS Estimation

	(1)	(2)	(3)
Total admissions	-0.058**	-0.049	-0.051*
	(0.028)	(0.031)	(0.029)
Injury	-0.066*	-0.078**	-0.079**
	(0.039)	(0.036)	(0.035)
Backache	-0.173***	-0.149***	-0.150***
	(0.039)	(0.044)	(0.044)
Mental disorders	-0.022	-0.002	-0.004
	(0.030)	(0.031)	(0.029)
Despair-related	-0.047	-0.038	-0.041
	(0.039)	(0.041)	(0.037)
Alcohol abuse	-0.077*	-0.089**	-0.091**
	(0.043)	(0.045)	(0.042)
Substance abuse	-0.045	-0.012	-0.015
	(0.045)	(0.049)	(0.044)
Opioid abuse	-0.057	-0.012	-0.015
	(0.060)	(0.064)	(0.061)
Suicide attempt	-0.104**	-0.062	-0.064
	(0.047)	(0.050)	(0.047)
Demographics	✓	✓	✓
Industry shares	✓	✓	✓
Import penetration		✓	✓
Log population			✓
Observations	90,862	90,862	90,862
CZs	376	376	376

Note: The data is from the 1996-2010 HCUP NIS. This table presents OLS estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions. All models include fixed effects for cohort $\times$ sex cells, hospitals, and year. All regressions are weighted by the population in cohort $\times$ sex cells within CZs. Standard errors clustered at the CZ level are in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.3.2 Alternative Sample

As noted in Section 2, data on nonfatal injuries are unavailable for certain states in specific years. To ensure consistency, our baseline analysis uses a balanced panel of 33 states. In Tables A.12 and A.13, we presents estimation results using all available states. Tables A.12 and A.13 demonstrate that our estimates of the impact of industrial robot exposure on workplace injuries in Tables 4 and 5 are robust to the sample choice.

Table A.12: Automation and Nonfatal Workplace Injuries
All Available States

	(1)	(2)	(3)	(4)	Mean
All nonfatal injuries	-0.460***	-0.425***	-0.293***	-0.295***	5.101
	(0.072)	(0.075)	(0.076)	(0.074)	
Nonfatal injuries by type					
Injury w/o lost workdays	-0.218***	-0.201***	-0.134**	-0.135**	2.533
	(0.051)	(0.054)	(0.053)	(0.052)	
Injury w / days of job transfer or restriction	-0.189***	-0.174***	-0.142***	-0.142***	1.038
	(0.027)	(0.029)	(0.026)	(0.026)	
Injury w / days away from work	-0.051*	-0.054*	-0.038	-0.039	1.531
	(0.030)	(0.031)	(0.032)	(0.028)	
Demographics		✓	✓	✓	
Industry shares			✓	✓	
Import penetration				✓	
Observations	621	621	621	621	
States	43	43	43	43	

Note: The data is from the 1996-2010 SOII. This table presents estimates of the effects of industrial robot exposure on nonfatal injury incidence per 100 FTE workers. All regressions are weighted by the state employment. Standard errors clustered at the state level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Automation and Fatal Workplace Injuries
All Available States

	(1)	(2)	(3)	(4)	Mean
All fatal injuries	0.219**	0.176	0.295*	0.295**	4.356
	(0.107)	(0.112)	(0.148)	(0.138)	
Fatal injuries by source					
Tools, instruments, and equipment	0.008	0.005	0.005	0.005	0.073
	(0.009)	(0.007)	(0.007)	(0.007)	
Machinery	-0.017	-0.016	-0.003	-0.003	0.337
	(0.013)	(0.015)	(0.020)	(0.020)	
Vehicles	0.128***	0.088*	0.152***	0.152***	1.893
	(0.046)	(0.047)	(0.056)	(0.053)	
Parts and materials	0.020*	0.024*	0.018	0.018	0.278
	(0.010)	(0.012)	(0.016)	(0.014)	
Containers	-0.006	-0.007	-0.005	-0.005	0.039
	(0.006)	(0.005)	(0.007)	(0.007)	
Structures and surfaces	0.021	0.025	0.044	0.044	0.625
	(0.014)	(0.019)	(0.029)	(0.027)	
Chemicals and chemical products	0.010	0.008	-0.005	-0.005	0.090
	(0.007)	(0.008)	(0.010)	(0.010)	
Persons, plants, animals, and minerals	0.029**	0.032**	0.032*	0.032*	0.198
	(0.011)	(0.012)	(0.018)	(0.018)	
Demographics		✓	✓	✓	
Industry shares			✓	✓	
Import penetration				✓	
Observations	765	765	765	765	
States	51	51	51	51	

Note: The data is from the 1996-2010 CFOI. This table presents estimates of the effects of industrial robot exposure on fatal injury incidence per 100,000 FTE workers. All regressions are weighted by state employment. Standard errors clustered at the state level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

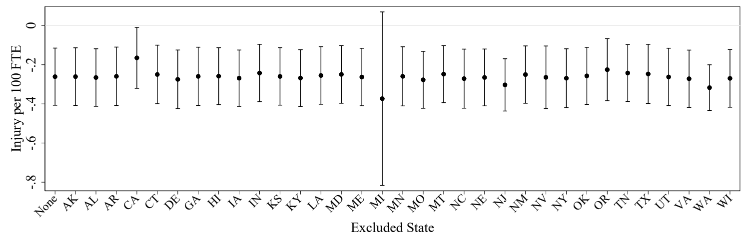
To further test whether the results are driven by any individual state or commuting zone, we conduct additional robustness analyses.

In Figure A.3, we present the results of leave-one-out analysis for the workplace injury regressions to confirm the robustness of our findings presented in Tables 4 and 5. Specifically, we re-estimate Equation (2) with one state excluded at a time. The estimates are robust to excluded states, with the exception of Michigan. However, the broad qualitative finding of a divergence in severity of occupational risks holds: we find a larger decrease in nonfatal injuries involving days away from work and a larger increase in fatal injuries due to automation.

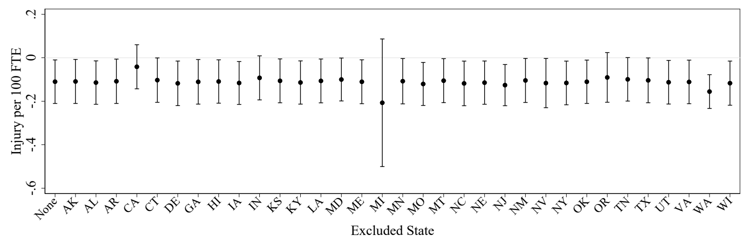
For hospitalization analyses, given a large number of CZs, we re-estimate Equation (3), excluding CZs with highest and/or lowest levels of automation exposure. In column (2), the analysis omits the top 1% of CZs with the highest average robot exposure during 1996–2010, whereas column (3) excludes the bottom 1% with the lowest exposure. Column (4) removes both the top and bottom 1% of CZs. Compared to the baseline estimates in column (1), excluding outliers do not have a significant impact on our qualitative and quantitative findings.

Figure A.3: Leave-one-out Test for Workplace Injuries

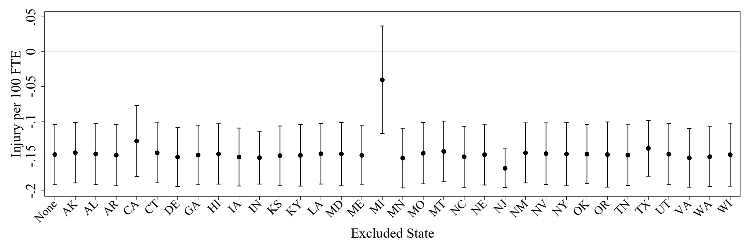
(a) All nonfatal injuries



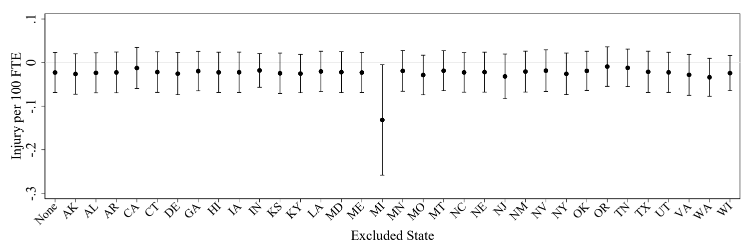
(b) Nonfatal w/o lost workdays



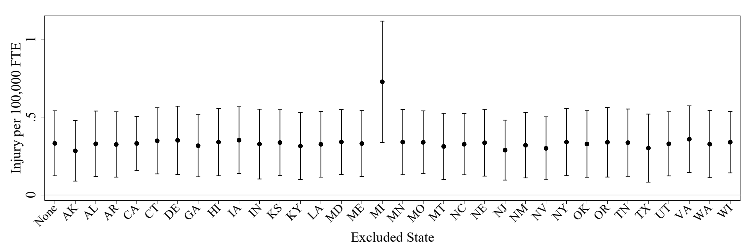
(c) Nonfatal w/ days of job transfer and restriction



(d) Nonfatal w/ days away from work



(e) All fatal injuries



Note: The data is from the 1996-2010 SOII and CFOI. This figure presents the estimates from the leave-one-out test for the effects of industrial robot exposure on nonfatal and fatal workplace injury rates 90% confidence intervals. All models include the full set of controls and fixed effects. All regressions are weighted by the state employment. Standard errors are clustered at the state level.

Table A.14: Automation and Hospitalization Discharges by Cause Excluding Outliers

	(1) Baseline	(2) Excl. high exposure	(3) Excl. low exposure	(4) Excl. high & low
Total admissions	-0.043	-0.042	-0.044	-0.043
	(0.030)	(0.031)	(0.030)	(0.031)
Injury	-0.160***	-0.178***	-0.161***	-0.178***
	(0.040)	(0.038)	(0.039)	(0.038)
Backache	-0.031	-0.043	-0.033	-0.045
	(0.034)	(0.034)	(0.033)	(0.034)
Mental disorders	-0.083*	-0.091*	-0.085*	-0.093*
	(0.050)	(0.053)	(0.051)	(0.053)
Despair-related	-0.074	-0.084	-0.075	-0.084
	(0.058)	(0.060)	(0.057)	(0.060)
Alcohol abuse	-0.123**	-0.137**	-0.123**	-0.137**
	(0.054)	(0.055)	(0.054)	(0.056)
Substance abuse	-0.080	-0.098	-0.081	-0.099*
	(0.060)	(0.061)	(0.059)	(0.060)
Opioid abuse	0.048	0.039	0.047	0.039
	(0.068)	(0.071)	(0.067)	(0.070)
Suicide attempt	0.023	0.011	0.025	0.012
	(0.060)	(0.062)	(0.059)	(0.061)
Observations	90,862	89,744	90,169	89,051
CZs	376	372	372	368

Note: The data is from the 1996-2010 HCUP NIS. This table presents estimates of the effects of industrial robot exposure on the log of 1 plus the number of hospitalizations with specific conditions. Column (2) shows the regression estimates excluding 1% of CZs with the highest robot exposure, Column (3) shows the regression estimates excluding 1% of CZs with the lowest robot exposure, and Column (4) shows the regression estimates excluding 1% of CZs with the highest and lowest robot exposure. All models include the full set of controls and fixed effects. All regressions are weighted by the population in cohort $\times$ sex cells within CZs. Standard errors clustered at the CZ level are in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$