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INDUSTRIAL ROBOTS, WORKERS' SAFETY, AND HEALTH

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ABSTRACT

This study explores the relationship between the adoption of industrial robots and workplace injuries. Using establishment-level data on injuries, we find that a one standard deviation increase in our commuting zone-level measure of robot exposure reduces work-related annual injury rates by approximately 1.2 cases per 100 workers. US commuting zones more exposed to robot penetration experience a significant increase in drug- or alcohol-related deaths and mental health problems. Employing longitudinal data from Germany, we exploit within-individual changes in robot exposure and document that a one standard deviation change in robot exposure led to a 4% decline in physical job intensity and a 5% decline in disability, but no evidence of significant effects on mental health and work and life satisfaction.

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1 Introduction

This paper studies the relationship between the adoption of industrial robots and workers' safety, health, and well-being. Robots and artificial intelligence are radically changing the role of workers in the production process, generating lively discussions on their effects on labor markets (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; de Vries et al., 2020; Dauth et al., 2021). The reallocation of tasks associated with automation is likely to have effects on work-related health risks. According to the Bureau of Labor Statistics (2020), private industry employers in the US reported over 5,000 fatal work-related injuries and 2.8 million nonfatal workplace injuries and illnesses in 2019, whose total estimated cost to the nation, employers, and individuals was $171 billion (National Safety Council, 2020), equivalent to 4% of 2019 US government budget. While the rapid adoption of industrial robots presents both new hopes and challenges to workers' safety and health (CDC, 2021), empirical evidence on robots' impacts on workplace safety and health remains sparse.

The relationship between robots and workers' physical health and safety is complex. On the one hand, since their introduction, industrial robots have typically been used for physically intensive tasks that are often associated with detrimental effects on health and increased risk of accidents at work.[1] In this context, automated systems can offer considerable safety benefits to human workers, as robots can help prevent injuries or adverse health effects resulting from working in hazardous conditions. Examples include musculoskeletal disorders due to repetitive or awkward motions (Schneider and Irastorza, 2010), or traumatic injuries (e.g., in poultry processing, where cuts are common). Robots can also prevent multiple hazards in emergency response situations such as chemical spills (Ishida et al., 2006). Besides protecting workers, robots can also minimize risks stemming from human error (Karwowski et al., 1988; Linsenmayer, 1985). If a job is repetitive and monotonous, humans tend to commit a mistake, whereas robots can do these things the same way repeatedly. On the other hand, robots can pose a variety of hazards to workers (Kirschgens et al., 2018). For example, while industrial robots have been designed to operate at a distance from workers, these machines often lack the sensory capabilities necessary to detect nearby humans. Moreover, the spread of collaborative robots, which are intended to di-

[1] See, for instance, https://www.designnews.com/automation-motion-control/robots-keep-workers-dangerous-tasks

rectly interact and share workspaces with humans, can lead to additional safety risks (Matthias et al., 2011). Therefore, the direction and the magnitude of the effects of robot adoption on workers' physical health are theoretically ambiguous and represent an open empirical question.

There is also increased concern that the complex relationship between humans and machines may have detrimental effects on workers' mental health (Robelski and Wischniewski, 2018) and act as an additional stressor at the workplace (Körner et al., 2019; Szalma and Taylor, 2011). Furthermore, the labor market effects of robot adoption and automation may increase stress and anxiety even among individuals who are not directly exposed (Venkataramani et al., 2020; Venkataramani and O'Brien, 2020).

In this study, we begin by investigating the relationship between the adoption of industrial robots and work-related injuries using data from the United States (US) and Germany, two of the leading robot adopters in the world. To examine the impact of robots on work-related injuries in the US, we use detailed establishment-level data on work injuries from the Occupational Safety and Health Administration (OSHA) Data Initiative (ODI) covering the 2005 to 2011 period, while information on the distribution of industrial robots across sectors and over time are sourced from the International Federation of Robotics (IFR).[2] Using establishment-level data on injury rates, we find that a one standard deviation increase in robot exposure (1.34 robots per 1,000 workers) reduces work-related injury rates by approximately 1.2 injuries per 100 full-time workers (0.15 standard deviations; 95% CI: -1.8, -0.53). To gauge the economic significance of the effects, a back-of-the-envelope calculation suggests that the increase in robots between 2005 and 2011 saved $1.69 billion per year in injury costs (in 2007 dollars). This result largely reflects a reduction in injury rates at manufacturing firms which decline by 1.75 injuries per 100 full-time workers (or 0.22 standard deviations; 95% CI: -2.48, -1.02). The results are robust to several sensitivity checks (for details, see Section 4.2).

We then turn to investigate whether robots have an impact on workers' mental health in the US. Using commuting zone-level data on mortality (source: The Centers for Disease Control and Prevention [CDC] Vital Statistics) and survey data on mental health problems (source: Behavioral Risk Factor Surveillance System [BRFSS]), we show that robot penetration leads to sizable increases in drug or alcohol-related deaths and mental health problems. A one standard de-

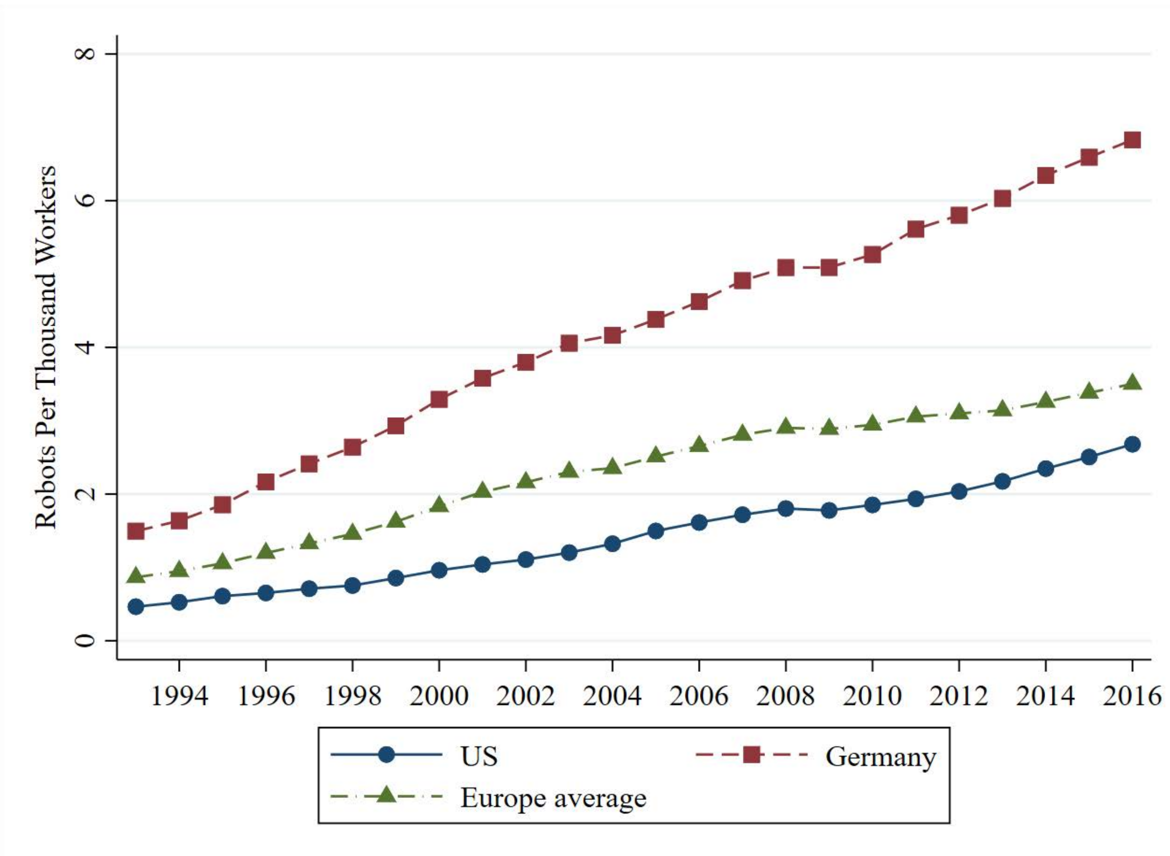
[2]Our analysis on establishment-level work injuries ends in 2011 because the ODI data was not collected after 2011.

viation increase in robot exposure raises deaths due to drug or alcohol abuse by 0.37 standard deviations (10.5% increase with respect to the mean) and the number of days during the previous month when the respondent felt his or her mental health was not good by 0.40 standard deviations (14.9% increase with respect to the mean). However, we find no evidence of significant effects on the suicide rate. Overall, we interpret these findings as evidence suggesting that the labor market pressure and fears induced by robot penetration (Acemoglu and Restrepo, 2020) may have detrimental effects on workers' mental health (see also Venkataramani and O'Brien (2020)).

Next, we leverage additional data from Germany to provide further evidence. Several reasons make Germany an appealing context to explore and complement the analysis based on the US establishment and regional data. First, Germany is a world leader in robotics whose robot penetration is even higher than that of the US, as shown in Figure 1. Second, evidence suggests that the effect of robot penetration on German manufacturing jobs was largely mitigated by the growth of jobs in services, thereby suggesting that the effects on mental health may be different compared to those observed in the US. Third, the availability of longitudinal survey data from the German Socio-Economic Panel (SOEP) containing information on occupation, sector, and various health and well-being outcomes allows us to shed further light on the complex effects of robot penetration on workers' safety using individual-level data and exploiting within-individual changes in exposure to robot penetration. Finally, using the SOEP data, we adopt an alternative identification strategy relying on the probability of exposure to robots based on the occupation associated with one's vocational training. Thus, we only leverage variation in robot exposure based on the track choice individuals made early in their life. This decision is unlikely to reflect correlates of robots' adoption and labor market outcomes later in life, and therefore, less likely to be endogenous.

The results based on the German individual panel data show that a one standard deviation increase in robot exposure is associated with a 0.01 standard deviations reduction in the risk of reporting any disability (-5% with respect to the mean) and a 0.02 standard deviations reduction in the likelihood of being employed in a highly physically intensive task (-4% with respect to the mean). We also find no evidence of significant effects of robot exposure on workers' well-being and mental health. Overall, our results for Germany are consistent with those documented by Dauth et al. (2021), who show that robot exposure did not cause disruptive job losses in Germany and that the individual risk of becoming unemployed is even lower among more robot-exposed manufacturing workers who were re-trained. They find that the longer-term shift from manufacturing to services was driven by young labor market entrants, not by actual switches. We argue that this is likely the main explanation for the different effects of robot exposure on mental health in Germany.

Figure 1: Trends in Robot Adoption in the US, Germany and Europe - 1993-2016



Notes - This figure shows the number of robots per thousand workers in the US, Germany, and European countries on average between 1993 and 2016. Data are drawn from the International Federation of Robotics.

Our methodological approach is closely connected to some recent studies analyzing the impact of robots on labor market conditions, life course choices, and demographic behavior. Recent studies have analyzed the effects of the increase in industrial robot usage on employment and wages across various countries (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Giuntella and Wang, 2019; Graetz and Michaels, 2018; de Vries et al., 2020). While Acemoglu and Restrepo (2020) and Giuntella and Wang (2019) estimate sizable and negative impacts of the rise in robot exposure on employment and wages across the US commuting zones and China, respectively, Dauth et al. (2021) and Graetz and Michaels (2018) find no significant effects on employment in Germany and for a set of 17 countries, respectively. Using data from 37 countries, de Vries et al. (2020) find that a rise in robot adoption reduces the employment share of routine manual jobs. Recent literature also examines the impact of robotization on family outcomes (Anelli et al., 2021). In a recent study, using data on self-reported health in the US and exposure to robots at the MSA-level, Gunadi and Ryu (2020) find that a 10% increase in robots per 1,000 workers is associated with approximately a 10% reduction in the fraction of low-skilled individuals reporting poor health. To the best of our knowledge, this is the only other study analyzing the relationship between robot penetration and physical health. Unlike Gunadi and Ryu (2020), we focus on establishment-level data on work-related injuries and use longitudinal data from Germany on both physical and mental health outcomes of workers. There are two other recent studies analyzing the relationship between automation and mental health. Venkataramani et al. (2020) find evidence of a strong association between automotive assembly plant closure and opioid overdose mortality between 1999 and 2016. In a concurrent work, Venkataramani and O'Brien (2020) show that robot penetration led to a substantial increase in drug overdose mortality between 1993 and 2007. While the present study examines a wider range of outcomes, our evidence on mortality in the US is largely consistent with their findings. Using data from Germany, Abeliansky and Beulmann (2019) find evidence of a decline in mental health associated with increased exposure to robots. While the latter study uses similar data for Germany, we adopt a different identification strategy and focus on a broader set of outcomes, and find no evidence of a decline in mental well-being.

By contrast, a growing number of studies investigate the effects of other labor market shocks on injuries and health (Colantone et al., 2019; Hummels et al., 2016; McManus and Schaur, 2016; Pierce and Schott, 2020). For instance, McManus and Schaur (2016) examine the effect of import competition in the US and find that an increase in import competition significantly increases worker injury and illness rates. Further, Hummels et al. (2016) exploit Danish employer-employee data combined with individual health data to demonstrate how rising exports may lead to increases in injuries, severe depression, and hospitalizations because of heart attack and strokes, whereas Colantone et al. (2019) explore the effects of exposure to global trade on mental health.

Pierce and Schott (2020) find that areas more exposed to international trade policy exhibit relative increases in fatal drug overdoses, specifically.

Our work also appeals to the recent few studies analyzing the effects of immigration on task allocation, work-related health risk, and the health of the native population (Giuntella and Mazzonna, 2015; Giuntella et al., 2019). Related to this literature, our study explores the effects of the changes in task allocation induced by robotization, and in particular, its effects on work-related accidents and mental health.

Finally, our study contributes to the literature that investigates the relationship between workers and machines, and their consequences on the health and mental well-being of workers. Robelski and Wischniewski (2018) provide a comprehensive review of the literature on human-machine interaction and physical and mental health, underlining the need for more research on the relationship between health and human-machine interaction.

The remainder of this paper proceeds as follows. Section 2 describes the data. We discuss the empirical strategy in Section 3. The evidence from the establishment and regional data for the US is presented in Section 4. In Section 5, we discuss the data and the empirical strategy, and report the results from the individual-level analysis in Germany. Section 6 concludes.

2 US Data

To study the relationship between robotization and workers' health and safety in the US, we employ data from the following sources: ODI, CDC, BRFSS, the American Community Survey (ACS), and IFR.

2.1 OSHA Data

Our primary data are drawn from the OSHA Data Initiative (ODI), which was established by OSHA. A unique feature of the ODI dataset is that it collects data on injuries and acute illnesses attributable to work-related activities at the establishment-level. The ODI collects workplace injury and illness data annually from approximately 80,000 employers. These data were collected to calculate establishment-specific injury and illnesses rates. The sample is restricted to firms with over 40–60 employees in high-hazard industries. The sample excludes industries not regulated by OSHA, such as mining and most government workers. The ODI dataset is an unbalanced panel: different establishments are included every year, with some overlapping across years. The establishments' data collected by OSHA through ODI present some important limitations. First, for each data collection cycle, OSHA only collects data from 1% of the total establishments (i.e., approximately 80,000 out of 7.5 million total establishments). Thus, the data are not representative of all businesses. OSHA takes multiple steps to ensure the quality of the data but acknowledges problems and errors may exist for a small percentage of establishments. Finally, not all states participate in the ODI survey. For instance, the data do not contain information for Alaska, Oregon, Puerto Rico, South Carolina, Washington, and Wyoming.[3]

Despite these limitations, the ODI dataset represents the only publicly available database including information on national establishment-level occupational injury and illness rates. Furthermore, while the ODI data are more likely to represent high injury and illness rate industries because of the survey exclusion criteria mentioned above, Neff et al. (2008) show that the state-level distributions of its findings do not differ dramatically from those obtained using the Survey of Occupational Injury and Illnesses. Finally, OSHA determines that the database is adequate for longitudinal analysis (Neff et al., 2008).[4]

The ODI survey provides data from 1996 to 2011, thereby allowing scholars to study trends and differences in private-sector occupational injury and illness rates.[5] In addition to including data on the establishment name, address, and industry, the ODI survey provides information on three key safety measurements: the associated total case rate (TCR), the days away, restricted, or transferred (DART) case rate, and the days away from work injury and illness (DAFWII) case rate. We use these safety metrics at the establishment-level as our main outcomes of interest.

In particular, while the TCR reflects the number of work-related injuries per 100 full-time workers during a one-year period, DART includes only those injuries that resulted in days away

[3]The sampling is based on censuses within industry and establishment-size groups, but some plants are automatically selected because of their injury records and other targeting strategies. Thus, yearly samples are partly selected as discussed in the paper, and unfortunately the selection rules are not fully disclosed and vary over time (see McManus and Schaur (2016)). The dataset is therefore partly biased towards high-injury plants. However, as documented by McManus and Schaur (2016), the correlation between industry-year TCR in the ODI sample and BLS population estimates is 0.9. We re-estimated the industry-year correlation between ODI and BLS official data (in our sample period), leading to a value of 0.93.

[4]See also https://clear.dol.gov/study/evaluation-osha%E2%80%99s-impact-workplace-injuries-and-illnesses-manufacturing-using-establishment.

[5]For simplicity, we refer to injuries and illnesses as "injuries." The ODI data was not collected after 2011.

from work, restricted work activity, or transfers to another job. Formally, DART is calculated using the following formula:

$$\frac{N}{EH} * 200,000 \tag{1}$$

where N is the number of cases involving days away and/or restricted work activity, and/or job transfers; EH is the total number of hours worked by all employees during the calendar year; and 200,000 is the base number of hours worked for 100 full-time equivalent employees during a one-year period.

DAFWII includes only days away from work per 100 full-time equivalent employees. Thus, it represents the more severe injuries, as cases requiring temporary transfers to another job or restricted work are excluded from this definition. Formally, DAFWII can be written as follows:

$$\frac{T}{EH} * 200,000 \tag{2}$$

where T is the number of cases involving days away from work; EH and the base number of hours per 100 full-time equivalent employees are defined in the same way as in formula (1).

It is worth remarking that the TCR, DART, and DAFWII measures are yearly rates of injuries at the establishment level, where the denominator is based on the number of the employees at a given establishment. Thus, when investigating the effect of robot penetration on these outcomes, we are not capturing a mechanical displacement effect. Summary statistics for the three safety metrics are reported in Panel A of Table A.1 in the Appendix.

2.2 Data on Mortality, Mental Health, and Occupational Burden

We collect data on the cause of death by county and year from the CDC and the National Center for Health Statistics using the CDC Wonder Online Database. Data are drawn from the detailed mortality file for the years 2005–2011. We restrict attention to deaths associated with drug and alcohol abuse and suicides and compute mortality rates per 100,000 inhabitants.

Information on mentally unhealthy days is drawn from the BRFSS, where individuals are asked to think about their mental health (including stress, depression, and problems with emotions), and report how many days during the last 30 days their mental health was not good. Data obtained from the BRFSS (2005-2011) are representative of each state's total non-institutionalized population over 18 years of age and have included more than 400,000 annual respondents with landline telephones or cellphones since 2011. We then aggregate county-year level data at the commuting zone-year level to conduct our analysis.

To measure physical and psychological burden, we employ the ISCO classification from the ACS and the General Index for Job Demands in Occupations constructed by Kroll (2011) and Giuntella et al. (2019), which associates a measure of the physical and psychological burden to each occupation on a 1–10 scale. We then aggregate the data at the commuting zone and year level to obtain the share of workers employed in jobs with a high physical and psychological burden (defined as a score above eight for both physical and psychological burdens).[6] Panel B of Table A.1 in the Appendix displays summary statistics on mortality and mental health.

2.3 Robot Data

Data on the stock of robots by industry, country, and year are drawn from IFR, a professional organization of robot suppliers established in 1987 to promote the robotics industry worldwide. These data are collected through a survey among IFR members, which gathers information on the number of robots that have been sold in a given industry and country. The data cover 70 countries over the period 1993 to 2016, accounting for more than 90% of the world market for robots. The IFR data report information on the operational stock of "industrial robots," defined as "automatically controlled, reprogrammable, and multipurpose machines" (IFR, 2016). Industrial robots are autonomous machines not operated by humans and can be programmed for several tasks, such as welding, painting, assembling, carrying materials, or packaging. By contrast, single-purpose machines, such as coffee machines, elevators, and automated storage systems are not robots based on this definition, because they cannot be programmed to perform other tasks, require a human operator, or both.

The IFR robot data are presently the best available data source on industrial robots. Moreover, this data source has been used by several scholars to analyze the labor market effects of industrial robots (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Giuntella and Wang, 2019; Anelli et al., 2021; de Vries et al., 2020; Graetz and Michaels, 2018). Nevertheless, the data do present several limitations. First, we only have information on the number of industrial robots

[6] Commuting zones can be regarded as local labor market areas.

by sectors for a sub-sample of countries for the period 1990–2003. In particular, for the US, the IFR dataset has information on the sectoral distribution of robots only since 2004, although information on the total stock of industrial robots is available since 1993. Second, the industry classifications are coarse with only 13 industrial sectors for manufacturing: food and beverages (1), textiles (2), wood and furniture (3), paper (4), plastic and chemicals (5), glass and ceramics (6), basic metals (7), metal products (8), metal machinery (9), electronics (10), automotive (11), other vehicles (12), and other manufacturing industries (13). For non-manufacturing sectors, data on the operational stock of robots are restricted to six broad categories, namely, agriculture, forestry and fishing, mining, utilities, construction, education, research and development, and other non-manufacturing industries (e.g., services and entertainment). Approximately, a third of the robots are not classified. These unclassified robots were allocated in the same proportion as in the classified data following Acemoglu and Restrepo (2020). An additional limitation of the IFR data is that the geographical information on the distribution of robots is available only at the country level. Nonetheless, we follow previous studies and construct a measure of robot exposure across regions (i.e., commuting zones), which we discuss in detail in the next section.

3 Empirical Strategy for the US Analysis

To investigate how robot exposure affects workers' health and safety, we estimate the following linear regression model:

$$Y_{ect} = \alpha + \beta(\text{Exposure to Robots})^{US}_{ct} + \tau_t + \eta_c + \epsilon_{ect} \tag{3}$$

where the subscript ect denotes an establishment e located in a commuting zone c in a given year t. Y_{ect} represents one of our workplace safety outcomes of interest, including, for instance, TCR, DART, and DAFWII case rates (detailed in the previous section). Our variable of interest is $(\text{Exposure to Robots})^{US}_{ct}$, which represents the exposure to robots of a commuting zone c at time t. For ease of interpretation, our measure of exposure to robots is expressed in units of its standard deviation in all our specifications.

The model in Equation (3) contains year fixed effects (τ_t) to account for possible trends in our outcomes. We also include a full set of commuting zone fixed effects (η_c) to control for unobservable time-invariant differences across commuting zones that may affect our outcomes of interest. Finally, ϵ_{ect} represents an idiosyncratic error term. Throughout the analysis, given that our measure of robot exposure varies at the commuting zone and year level, we cluster standard errors at the commuting zone level. We show that the significance of the results is robust to the use of wild cluster bootstrap standard errors (Cameron et al., 2008).[7]

We measure robot penetration following Acemoglu and Restrepo (2020). Therefore, we exploit the pre-existing distribution of employment across commuting zones and industries and multiply it by the national level evolution in the number of robots across industries. As most of the rise in industrial robots in the US occurred after 1990, we choose 1990 as the baseline year. In practice, we compute the ratio of robots to employed workers in industry s at the national level and multiply it by the commuting zone's baseline employment share in sector s, and then sum separately for each commuting zone, over all sectors. Formally, our measure of exposure to robots is constructed as follows:

$$\text{Exposure to Robots}_{c,t}^{US} = \sum_{s \in S} l_{cs}^{1990} \left(\frac{R_{s,t}^{US}}{L_{s,1990}^{US}} \right) \tag{4}$$

where l_{cs}^{1990} denotes the 1990 distribution of employment across industries and commuting zones; $R_{s,t}^{US}$ identifies the stock of robots in the US across industries in year t; and $L_{s,1990}^{US}$ represents the total number of individuals (in thousands) employed in sector s in 1990. Our identification largely exploits the variation in robot exposure across commuting zones and over time. This variation hinges on the differences across industries over time in the adoption of industrial robots and the initial distribution of sectoral employment across commuting zones.

Figure 2 illustrates the gradual growth in robot adoptions between 2004 and 2016, comparing manufacturing sectors with all the other industries. Manufacturing (left-axis) has, by far, the highest number of robots per thousand workers (approximately 13 robots per thousand workers in 2016) as opposed to other sectors (approximately 0.2 robots per thousand workers in 2016).

The measure of exposure to robots is based on the initial employment shares in the commuting zone: a Bartik-type instrument. However, to mitigate concerns about the potential correlation

[7]Furthermore, the significance of our main results is largely unaffected when we cluster standard errors by state instead of commuting zone (Acemoglu and Restrepo, 2020).

of our measure of robot exposure with other factors that may also affect work-related injuries, we follow Acemoglu and Restrepo (2020) and use the industry-level robot installations in other economies, which are meant to proxy improvements in the world technology frontier of robots, as our instrumental variable (IV) for the adoption of robots in the US. In practice, we use the average robot exposure at the industry-level in the nine European countries that are available in the IFR data over the same period.[8] The underlying idea is to exploit only the variation in the increase in robot adoption across industries of other countries. Our instrument for exposure to robots is defined as follows:

$$\text{Exposure to Robots}_{c,t}^{IV} = \sum_{s \in S} l_{cs}^{1970} \left(\frac{R_{s,t}^{p30,EU}}{L_{s,1990}^{EU}} \right) \tag{5}$$

where the sum runs over all industries available in the IFR data, l_{cs}^{1970} represents the 1970 share of employment in commuting zone c and industry s, as calculated from the 1970 Census, and $\frac{R_{s,t}^{p30,EU}}{L_{s,1990}^{EU}}$ denotes the 30th percentile of robot exposure among the above-mentioned European countries in industry s and year t.[9]

Model (3) is estimated using two stage least squares (2SLS), and the first-stage regression is given by:

$$\sum_{s \in S} l_{cs}^{1990} \left(\frac{R_{s,t}^{US}}{L_{s,1990}^{US}} \right) = \pi_0 + \pi_1 \left[\sum_{s \in S} l_{cs}^{1970} \left(\frac{R_{s,t}^{p30,EU}}{L_{s,1990}^{EU}} \right) \right] + \delta_t + \sigma_c + v_{ct} \tag{6}$$

where $\sum_{s \in S} l_{cs}^{1990} (\frac{R_{s,t}^{US}}{L_{s,1990}^{US}})$ is instrumented with $[\sum_{s \in S} l_{cs}^{1970} (\frac{R_{s,t}^{p30,EU}}{L_{s,1990}^{EU}})]$, the industry-level robot exposure variable based on the adoption of robots across sectors in the above-mentioned European countries. δ_t, σ_c, and v_{ct} are defined in the same way as in Model (3).

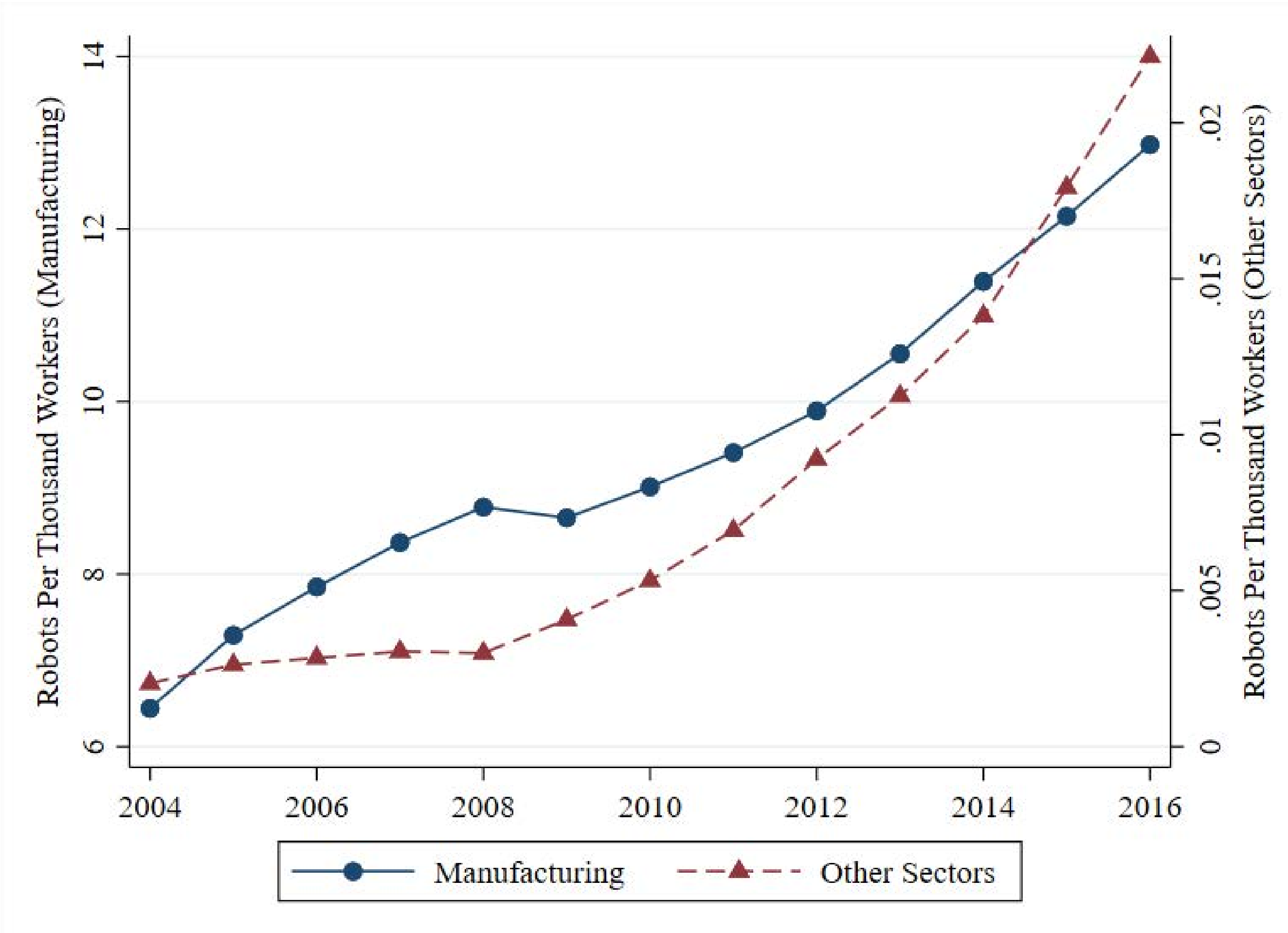
We adopt a similar estimation strategy when using individual-level data from Germany. However, as explained in Section 5, in the case of Germany, we use an individual fixed effect strategy, exploiting within-individual variation in exposure to robots over time based on the individual sector as of 1994. Furthermore, we also propose an alternative identification strategy allocating the inflows of robots based on the occupation associated with an individual's school

[8]The nine European countries are France, Denmark, Finland, Italy, Germany, Norway, Spain, Sweden, and the United Kingdom.

[9]Following Acemoglu and Restrepo (2020), we used the 30th percentile as the US robot adoption closely follows the 30th percentile of the EU robot adoption distribution.

track and vocational training, and restrict the sample to individuals who were born before 1981 and thus entered the tracking system in the early ’90s.

Figure 2: Evolution of Industrial Robots in the US, Manufacturing vs. Other Sectors



Notes - This figure shows the number of robots per thousand workers in the US separately for the manufacturing sector (left vertical axis) and other (non-manufacturing) sectors (right vertical axis) during 2004-2016. Data are drawn from the International Federation of Robotics.

4 Results for the US

4.1 Effects on Work-Related Injuries

In Table 1, we explore the direct effect of robot exposure on our primary three workplace safety outcomes: TCR, DART, and DAFWII (see Panels A, B, and C, respectively). In these regressions, we use the ODI data and include year and commuting zone fixed effects. Columns 1 and 2 report the ordinary least squares (OLS) and reduced form coefficients, while the 2SLS estimates are presented in column 3. The first-stage F statistic reported at the bottom of each Panel is well above the conventional levels (see also the first stage relationship presented in Table A.2 in the Appendix). The magnitude of 2SLS and OLS estimates is fairly similar. This is not surprising because our measure of robot exposure is already a Bartik-type instrument, which exploits the geographical distribution of sectors in the base-year to allocate robots across US commuting zones.

Overall, Table 1 documents a negative and highly significant impact of robot exposure on TCR. Focusing on the IV estimate in column 3 of Panel A, we find that a one standard deviation increase in our measure of robot exposure decreases the number of workplace injuries by 1.169 per 100 full-time workers during a one-year period, which is equivalent to approximately 16% of the mean in our sample (7.132 cases per 100 workers). Similarly, as shown in Panel B, establishments based in commuting zones that are more exposed to robot penetration experience a significant reduction in the number of injuries that result in DART. Specifically, a one standard deviation increase in robot exposure decreases the DART rate by 0.84 injuries per 100 full time workers, equivalent to 20% for the mean of the dependent variable (4.187 cases per 100 workers). By contrast, in Panel C, we find no evidence of significant impacts of robot exposure on the most serious injuries, that is, DAFWII.[10]

To gauge a sense of the economic magnitude of these effects, we conducted a back-of-the envelope calculation. Throughout the period, the stock of robots increased from an average of 1.34 robots per 1,000 workers in 2005 to 1.71 robots per 1,000 workers in 2011, increasing by roughly 25% with respect to the mean over this period of time (a change equivalent to approximately

[10] Arias (2014) argues that DAFWII is prone to measurement issues due to possible data reporting problems. In fact, in their study on import competition and worker health, McManus and Schaur (2016) consider only TCR and DART, which they interpret as their measure of "severe injury rate."

Table 1: Effects of Robot Exposure on Workplace Injuries

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: TCR			
Robot exposure	-1.559***		-1.169***
	(0.375)		(0.321)
Robot exposure - IV		-0.495***	
		(0.139)	
Mean of dep. var.	7.132	7.132	7.132
Std. dev. of dep. var.	8.235	8.235	8.235
R-squared	0.051	0.051	0.017
First stage F statistic			681.1
Panel B: Dep. var.: DART			
Robot exposure	-1.010***		-0.841***
	(0.224)		(0.207)
Robot exposure - IV		-0.356***	
		(0.088)	
Mean of dep. var.	4.187	4.187	4.187
Std. dev. of dep. var.	5.429	5.429	5.429
R-squared	0.040	0.040	0.015
First stage F statistic			681.1
Panel C: Dep. var.: DAFWII			
Robot exposure	-0.020		0.132
	(0.151)		(0.132)
Robot exposure - IV		0.056	
		(0.057)	
Mean of dep. var.	2.150	2.150	2.150
Std. dev. of dep. var.	3.398	3.398	3.398
R-squared	0.037	0.037	0.006
First stage F statistic			681.1
Observations	445,562	445,562	445,562

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

.28 standard deviations). Given these numbers, we estimate that the increase in the adoption of robots between 2005 and 2011 led to a reduction of 0.33 injuries per 100 workers over time.[11] Given that 153.5 million persons worked at some point during 2011 (Bureau of Labor Statistics, 2011)[12], this implies 508,611 if less injuries between 2005 and 2011, or 72,658 less injuries per year. Leigh (2011) estimates that each injury case costs $23,000 of damage in 2007 dollars. Using this estimate, we calculate that the increase in robots observed between 2005 and 2011 saved $11.69 billion throughout the period, or $1.67 billion per year in 2007 dollars (or 0.065% of the 2007 US government budget). For comparison, Lai et al. (2019) estimate that the increase in Chinese imports saved $1.58 billion in injury costs per year in 2007 dollars.

It is worth remarking that our three injury outcomes are measured as rates out of the total number of workers at the establishment. Therefore, these results are not driven by mere displacement effects. In other words, conditional on the same number of workers, in areas where robot penetration increased, the number of injuries declined.

As a falsification test, we analyzed the relationship between robot adoption and lagged injury rates. A significant relationship would cast doubt on our identification assumption suggesting that areas that were more exposed to robot penetration between 2005 and 2011 may have already been on differential trends with respect to injury rates. When regressing the change in work-related injuries between 1996 and 2001 on the change in robot exposure between 2005 and 2011, we find that the OLS and reduced form coefficients on TCR and DART become much smaller and no longer significant, yielding further support to the causal interpretation of our estimates (see Table 2).[13]

As previously mentioned, we hypothesize that the reduction in injuries may be driven by a reallocation of tasks in production, with robot penetration leading workers toward less physically intensive tasks and jobs. In Table 3, we explore the potential mechanism underlying the reduction in occupational injury using ACS data at the commuting zone level over the 2005–2011 period. We find a negative effect on total job burden, measuring both physical and psycholog-

[11] This is obtained multiplying the change in robots per 1,000 workers (.37) by the coefficient of our baseline estimate on TCR (1.2, see column 1 of Table 1), divided by the standard deviation (1.34).

[12] Bureau of Labor Statistics, US Department of Labor, The Economics Daily, Employment and Unemployment Experience of the US Population in 2011, available at: `https://www.bls.gov/opub/ted/2012/ted_20121227.htm` (visited on October 2, 2021)

[13] ODI data are available since 1996 for TCR and DART. Data on DAFWII for the period 1996-2001 are not available. However, the effects of robot exposure on DAFWII in our baseline estimates were not statistically significant.

Table 2: Falsification test: Robot Exposure (2005-2011) and Pre-Trends (1996-2001) in Injuries (Commuting-Zone Level)

	(1)	(2)	(3)	(4)
Dep. var.:	Change in TCR		Change in DART	
	$\Delta_{2001-1996}$		$\Delta_{2001-1996}$	
	OLS	Reduced form	OLS	Reduced form
Change in robot exposure	0.003		0.006	
($\Delta_{2011-2005}$)	(0.010)		(0.012)	
Change in robot exposure - IV		0.062		-0.004
($\Delta_{2011-2005}$)		(0.070)		(0.031)
Observations	596	596	596	596
Mean of dep. var.	-0.062	-0.062	0.015	0.015
Std. dev. of dep. var.	1.540	1.540	0.741	0.741

Notes - Data are drawn from the ODI (OSHA) dataset. The unit of observation is at the commuting zone level. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

ical burden. We define high total burden as a dummy variable equal to one if the continuous indicator of total burden is larger than eight (i.e., the 75th percentile). However, the coefficient is not precisely estimated. In column 2, the 2SLS estimate suggests that a one standard deviation increase in robot exposure is associated with a 6.3% reduction in the likelihood of working in a highly physically intensive occupation (defined as physical burden above 8), whereas we find no evidence of significant effects on the high occupational psychological burden (defined as psychological burden above 8, see column 3). As shown in Table A.3 in the Appendix, these results are driven by the most physically intensive jobs.

It is worth noting that the analysis of physical and psychological burden only captures changes across occupations. Previous studies have shown that the reallocation of risk within an occupation title can be significant, and it is likely the case that the adoption of robots induced a reallocation of workers to less physically intensive tasks within a job, and not just a reallocation of workers to different occupational titles (Giuntella and Mazzonna, 2015).

Table 4 reports the 2SLS estimates of the effects of robot exposure on workplace injuries by the industrial sector. Specifically, focusing on TCR as our dependent variable (see Panel A), we find that the overall effects are driven by the manufacturing sector (see column 3). A one standard deviation increase in robot exposure reduces the number of workplace injuries in the

Table 3: Robot Exposure, Physical and Psychological Burden - 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	High total burden	High physical burden	High psychological burden
Robot exposure	-0.008	-0.015***	0.004
	(0.005)	(0.005)	(0.005)
Observations	5,187	5,187	5,187
Mean of dep. var.	0.296	0.236	0.155
Std. dev. of dep. var.	0.043	0.046	0.021
R-squared	0.013	0.041	0.014
First stage F statistic	577.2	577.2	577.2

Notes - Data are drawn from the American Community Survey (2005-2011). The unit of observation is at the commuting zone-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

manufacturing sector by 1.75 injuries per 100 workers, which corresponds to approximately 28% relative to the mean outcome (6.349). We obtain a similar finding when we consider DART as the dependent variable: the 2SLS estimate reported in column 3 of Panel B suggests that a one standard deviation increase in robot exposure leads to a decrease in DART of about 34% relative to the average DART. It is reassuring that we find no evidence of significant effects in sectors that are less exposed to the penetration of industrial robots (see column 6). It is worth noting that the health care sector comprises 97% of the establishments in the service industry surveyed in the ODI dataset.

4.2 Sensitivity Analysis

In what follows, we perform a variety of robustness checks to test how the results change when we modify the sample or use a different specification compared to our benchmark model (see Table 1). First, we show that our estimates of the effects of robot exposure on workplace injuries are robust to aggregating the data at the commuting zone and year level (see Table A.4 in the Appendix). Second, in Table A.5 in the Appendix, we illustrate that the main results are not affected by the inclusion of state-specific time trends, which are meant to capture unobserved cross-state differences in work-related injuries over time. Third, as individuals may need additional time to adjust their health behavior in response to robot exposure, we re-estimate our

Table 4: Effects of Robot Exposure on Workplace Injuries, by Industrial Sector - 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Agriculture	Construction	Manufacturing	Transportation	Retail & Wholesale Trade	Services
			Panel A: Dep. var.: TCR			
Robot exposure	-4.822	-1.214	-1.752***	0.226	0.255	-0.422
	(3.439)	(10.303)	(0.372)	(1.173)	(0.533)	(0.722)
Mean of dep. var.	7.351	6.031	6.349	7.605	7.507	10.15
Std. dev. of dep. var.	8.188	7.411	7.865	7.925	6.805	10.61
R-squared	0.016	0.001	0.020	0.021	0.022	0.004
First stage F statistic	850	81.59	858.9	361.6	442.3	395.3
			Panel B: Dep. var.: DART			
Robot exposure	-2.611	4.848	-1.171***	0.057	0.324	-0.524
	(2.443)	(5.246)	(0.237)	(0.765)	(0.312)	(0.607)
Mean of dep. var.	4.321	3.190	3.420	5.170	4.775	6.500
Std. dev. of dep. var.	5.625	4.169	5.106	6.121	5.027	6.072
R-squared	0.010	0.000	0.017	0.018	0.014	0.005
First stage F statistic	850	81.59	858.9	361.6	442.3	395.3
Observations	5,373	14,819	260,306	43,755	63,100	57,951

Notes - Data are drawn from the ODI (OSHA) dataset (2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

baseline specification using a one-year lagged measure of robot exposure as the main explanatory variable (see Table A.6 in the Appendix). Reassuringly, the results substantially confirm the findings presented in our main analysis. Fourth, in Table A.7 we show that the inclusion of time-varying, commuting-zone level socio-demographic controls, such as the share of women, the average age and the proportion of individuals with a college degree, did not alter the main results. Moreover, while we only have data on the sectoral distribution of robots in the US since 2004, we follow Acemoglu and Restrepo (2020) and use the sectoral distribution of robots in Europe (our IV) to explore the reduced form relationship between robot penetration in Europe and work-related injuries in the US over a longer period (1996–2011).[14] As displayed in Table A.8, the reduced form point estimates are slightly larger than the ones presented in column 2 of Table 1, suggesting that a one standard deviation in robot exposure reduces TCR by 0.782 cases per 100 workers (equivalent to 7.9% relative to the mean outcome) and the DART rate by 0.529 cases per 100 workers (equivalent to 9.6% relative to the mean outcome). Next, we check the sensitivity of the reduced form estimates to the exclusion of the recession period. Overall, the estimates reported in Table A.9 confirm that firms in commuting zones with a higher robot penetration experience a decline in work-related injuries.

As a further robustness check, we estimate Model (3) including establishment fixed effects, which allow us to net out the confounding effects of any time-invariant characteristic across establishments. Reassuringly, the 2SLS estimates presented in Panel A of Table A.10 in the Appendix demonstrate that the effects of robot exposure are very similar to the benchmark specification. Finally, we exploit the sectoral information available in the ODI dataset to construct an alternative measure of robot exposure that varies by sector and year. In this case, we create a metric of sectoral exposure at the national level and assign it to each establishment in a given sector. The 2SLS coefficients displayed in Panel B of Table A.10 are overall consistent with those obtained using the geographical measure of robot exposure at the commuting zone level. Specifically, we find that a one standard deviation increase in sectoral robot exposure leads to a 1.649 reduction in the number of injury cases per 100 workers, which is equivalent to a 21.6% reduction for the mean outcome.

To address the concern that our results may be confounded by differential trends experienced

[14]ODI data are available since 1996 for two of the safety outcomes, namely, TCR and DART.

by some industries, we calculated the Rotemberg weights following the methodology described in Goldsmith-Pinkham et al. (2020).[15] We find that the electronics sector has, by far, the largest weight in our identification strategy during our period of interest (see Table A.11 in the Appendix). Reassuringly, results are robust when controlling for area-specific trends across areas with low and high initial shares of employment in the electronics sector or when removing establishments in the electronics sector (see Panels A and B of Table A.12 in the Appendix). Moreover, we show that the results are largely unchanged when including specific time trends across areas with different initial shares of the automotive sector employment, the sector that adopted most robots throughout the period of study (see Table A.13 in the Appendix).

One may be worried that our measure of robot exposure could be correlated with other economic shocks, particularly to the exposure to import competition from China (Autor and Dorn, 2013). Acemoglu and Restrepo (2020) and Anelli et al. (2019) illustrate that the trade shock is orthogonal to the adoption of robots for both the US and Europe. These studies document how industries that strongly robotized production processes were generally industries that did not offshore production. However, we also show that our results are robust to the inclusion of controls for exposure to trade penetration (see Panel A of Table A.14).[16] As a further check, in Panel B of Table A.14 in the Appendix we also show that our findings are not affected by the inclusion of time-specific trends interacted with the 1990 share of employment in total manufacturing. Finally, results are also robust to the inclusion of region-year fixed effects (see Panel C), and are substantially unaltered when including industry-year fixed effects (see Panel D).

As injuries are notoriously skewed, we also conducted alternative estimations obtained by topcoding the dependent variables at the 99^{th} percentile. Results of this analysis presented in Panel A of Table A.15 are similar to the baseline. Furthermore, results tend in the same direction when considering the outcomes in logarithms (see Panel B) or using the inverse hyperbolic sine

[15]Specifically, we used the Bartik weight ado file made available by Paul Goldsmith-Pinkham. For details, see `https://github.com/paulgp/bartik-weight`.

[16]To measure trade penetration, we followed Pierce and Schott (2020) and computed exposure to Chinese imports by looking at the difference between tariff rates set by the Smoot-Hawley Tariff Act and the corresponding NTR (normal trade relations) tariffs. In 2000, the US passed a bill granting normal trade relations to China. This trade liberalization affected differentially US regions depending on their industry structure. A larger difference between the non-NTR rates and the NTR rates implied a larger potential for Chinese exporters increasing import competition for US producers in a given sector. Consistent with Pierce and Schott (2020), we calculated the commuting zone-level exposure to import penetration using the labor-share-weighted average NTR gaps of the industries active within a commuting zone in 1990. We then interacted this commuting zone-level measure of exposure to trade with year dummies.

transformation (see Panel C), although the effect on DART is less precisely estimated (p-values equal 0.14 and 0.17, respectively). Table A.16 shows that the significance of our main results does not vary substantially when using wild cluster bootstrap standard errors.

4.3 Effects on Drug- and Alcohol-Related Deaths and Suicides

On the one hand, robots may have reduced the risk of injuries and the overall physical intensity of job tasks, while on the other hand, they may have increased job precariousness and workers' uncertainty. Acemoglu and Restrepo (2020) find significant negative effects of robot exposure on income and hours worked, and a positive effect on unemployment.[17] These results are consistent with the reasoning that at least in the short-run, robots may have increased uncertainty on labor market opportunities, and thus, may have contributed to increased pressure on workers, similar to what is documented when examining the effects of trade and other labor market shocks on workers' mental health (Colantone et al., 2019) and found by Venkataramani et al. (2020) when examining the association between plant closures and opioid overdose mortality.

To analyze the effects of robot exposure on the mental health of workers, we merged the IFR data with commuting zone-level data on the reason of death (CDC), and BRFSS data aggregated at the commuting zone-level on the number of mentally unhealthy days. All these estimates are weighted by the commuting zone-level population. We focus on deaths due to drug or alcohol abuse and suicides. The results of this analysis are reported in Table 5.

Panel A of Table 5 documents a positive and significant relationship between the exposure to industrial robots and the rate of deaths due to drug or alcohol abuse. The OLS estimate in column 1 suggests that a one standard deviation increase in robot exposure is associated with an increase of 37.8 cases per 100,000 inhabitants (equivalent to 9.6% relative to the mean of the dependent variable). The average increase in robots per 1,000 workers throughout the period (0.37) would lead to an increase of approximately 10.2 cases per 100,000 inhabitants (or a 3% increase with respect to the mean). The 2SLS estimate displayed in column 3 is only slightly larger, suggesting a 10.5% increase with respect to the mean. In Panel B, we examine the relationship between robot exposure and suicide rates. We find no evidence of significant effects

[17] We replicate their analyses on wages and employment and confirm significant negative effects of robot exposure on labor market outcomes. Results are available upon request.

Table 5: Effects of Robot Exposure on Deaths due to Drug or Alcohol Abuse, Suicide Rate, and Mental Health

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Deaths due to drug or alcohol abuse			
Robot exposure	37.841***		41.436***
	(5.464)		(5.732)
Robot exposure - IV		17.053***	
		(2.027)	
Observations	4,607	4,607	4,607
Mean of dep. var.	390.6	390.6	390.6
Std. dev. of dep. var.	110.8	110.8	110.8
R-squared	0.954	0.954	0.048
First stage F statistic			489.5
Panel B: Dep. var.: Deaths due to suicides			
Robot exposure	0.397		0.339
	(0.567)		(0.685)
Robot exposure - IV		0.139	
		(0.286)	
Observations	1,379	1,379	1,379
Mean of dep. var.	14.47	14.47	14.47
Std. dev. of dep. var.	4.954	4.954	4.954
R-squared	0.853	0.853	0.154
First stage F statistic			388
Panel C: Dep. var.: Number of mentally unhealthy days			
Robot exposure	0.312**		0.555***
	(0.134)		(0.153)
Robot exposure - IV		0.233***	
		(0.062)	
Observations	4,245	4,245	4,245
Mean of dep. var.	3.713	3.713	3.713
Std. dev. of dep. var.	1.384	1.384	1.384
R-squared	0.448	0.449	0.037
First stage F statistic			407

Notes - Data on reason of death (Panels A and B) are drawn from Vital Statistics (CDC). Data on the number of mentally unhealthy days are drawn from the BRFSS (Panel C). The unit of observation is at the commuting zone-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level. All estimates are weighted by the commuting zone-level population.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

on suicide rate, although the point estimate indicates that areas that are more exposed to robot penetration experience a slight increase in suicide rate (+2.3%).[18] Similarly, we find a positive but non-significant coefficient when measuring the relationship between robot penetration and psychological burden (see column 3 of Table 3).

Finally, Panel C shows a positive relationship between robot exposure and the number of mentally unhealthy days. The 2SLS estimate in column 3 indicates that a one standard deviation increase in robot exposure leads to a 0.555 increase in the number of days in the past 30 days that individuals reported mental health as not being good, which is equivalent to a 14.9% increase for the mean outcome. Equivalently, the average increase in robots per 1,000 workers throughout the period (0.37) would lead to a 4% increase in the number of mentally unhealthy days with respect to the mean.

As for injury rates, we show that the results on substance abuse, suicides, and mental health are largely robust to controlling for specific trends across areas with high and low initial shares of employment in the electronics sector, removing establishments in the electronics sector, as well as controlling for the exposure to trade penetration and specific trends in the manufacturing sector (see Panels A-D of Table A.17 in the Appendix).

5 Individual-Level Data from Germany

As mentioned in Section 1, Germany has been a leader in robotics since the early '90s, thereby providing a very interesting context to study the effects of robots on workers' health and safety. Furthermore, the availability of a longitudinal dataset with information on workers' industrial sector, health, and well-being allows us to exploit within-individual variation in the exposure to robots over time and investigate how robots affect workers' health over more than 20 years.

[18] It is worth noting that the sample size reduces substantially, as we only have information on suicides on a restricted sample of counties (542).

5.1 Data and Empirical Specification for Germany

5.1.1 Data

To analyze the relationship between robot exposure and workers' health and safety in Germany, we employ data from the SOEP, a longitudinal dataset of the German population containing information on a rich set of individual socioeconomic characteristics since 1984.[19] The SOEP consists of several subsamples and is constructed to ensure it is representative of the entire population of Germany. For a detailed description of the survey, see Wagner et al. (2007) and Goebel et al. (2019). The SOEP provides information on several health metrics (including self-assessed health status, satisfaction with health, and mental and physical health). In this study, we focus on two main health outcomes: a dummy variable equal to one for a doctor-assessed disability, and an indicator variable taking value one if the individual reported a work accident that required treatment by a doctor or at a hospital. While information about disability status is available from 1984 onward, respondents were asked about their accidents at work only during the years between 1987 and 1999. Furthermore, the SOEP data contains information on individual labor market histories and the worker's industrial sector based on the NACE 2-digit classification, which we use to merge with the data on robots from the IFR. To estimate our model, we construct an unbalanced panel of manufacturing and non-manufacturing workers from 1994 through 2016, thereby covering the period for which we have IFR data on the stocks of industrial robots by sector in Germany.[20]

5.1.2 Empirical Specification

To dispel the concern that individual sorting across sectors as a response to robots may invalidate our identification strategy, our measure of individual exposure to robot penetration is based on the sector in which workers were employed in 1994. We restrict the sample to individuals observed in 1994 (N=17,810).[21] Thus, our metric of robot penetration in Germany is based

[19]The data version used in this paper is SOEP version 35, SOEP, 2020, doi: 10.5684/soep.v35.

[20]While we do have information on robots since 1993, information on disability and work-related injuries is not available in the 1993 SOEP wave.

[21]Individuals who were unemployed in 1994 were assigned their first available industrial sector. Results are substantially identical if we restrict the sample to individuals employed in 1994 and assign robot exposure based on their occupation in 1994 (available upon request).

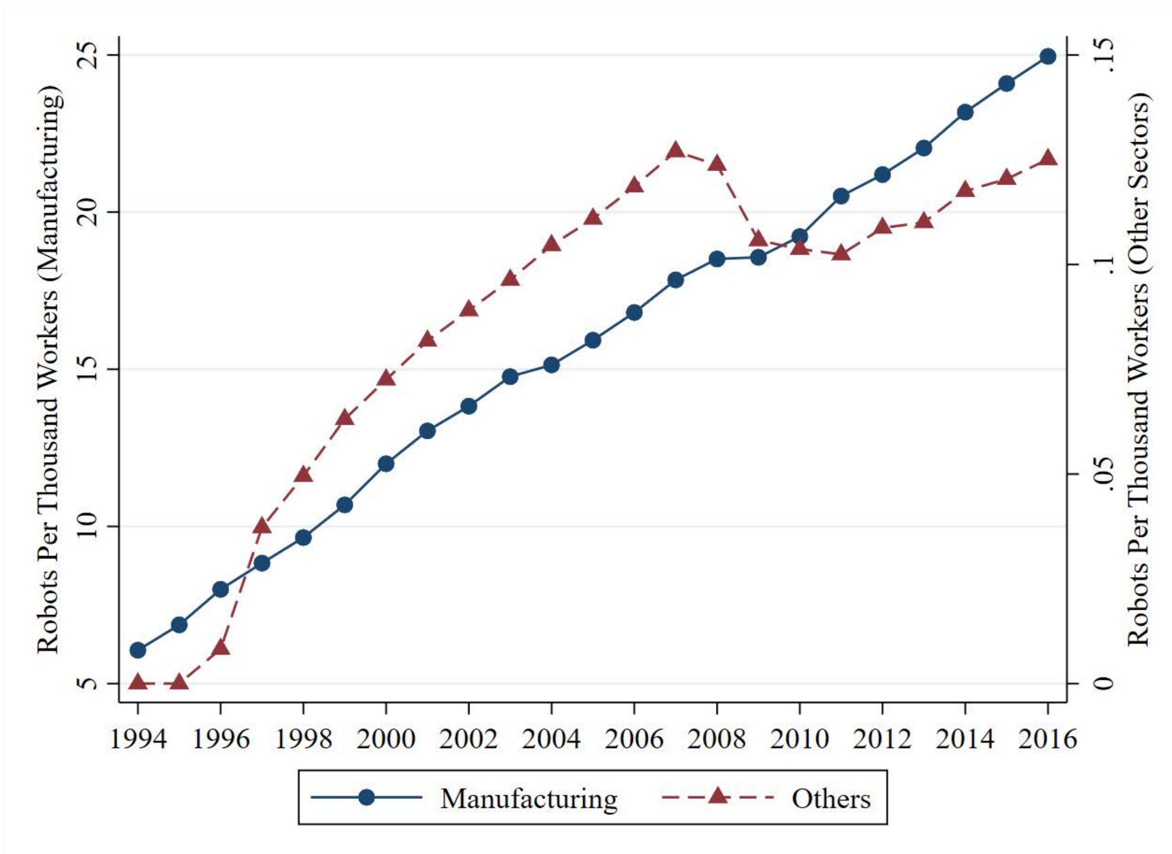
on the sector of employment at baseline and the variation over time in the adoption of robots across sectors. We then follow individuals over time and exploit the within-individual variation over time in robot exposure to identify its effects on the likelihood of reporting any disability, and our measure of occupational physical intensity. After restricting the sample to workers who were SOEP respondents in 1994, were aged 18–64 during the years in which outcomes were measured, and were not self-employed, we obtain a final longitudinal sample containing 64,358 person-year observations resulting from 6,228 individuals. Table A.18 in the Appendix reports descriptive statistics on the main variables used in the analysis. Figure 3 illustrates the trends in robot adoption in Germany, comparing manufacturing industries vs. all the other sectors. As is evident from the figure, there is a marked difference in the levels of robot penetration between manufacturing and the other sectors, while the growth rate is relatively similar.

We estimate the following linear regression model:

$$Y_{ijrt} = \alpha + \beta(\text{Exposure to Robots})^{GE}_{jt} + \lambda X_{it} + \gamma_i + \tau_t + \eta_r + \epsilon_{ijrt} \quad (7)$$

where the index $ijrt$ denotes an individual i, working in IFR sector j in federal state r at the year of interview t. The outcome variable Y_{ijrt} represents an indicator variable for an individual who reported a disability, high physical burden (defined as a dummy variable if the physical burden is above 8), high psychological burden (defined as a dummy taking the value one if the psychological burden is above 8), work satisfaction, and life satisfaction. Our variable of interest is $(\text{Exposure to Robots})^{GE}_{jt}$, which represents the robot adoption in industry j and year t. For ease of interpretation, our measure of exposure to robots is expressed in units of its standard deviation in all our specifications. In the vector X_{irt}, we include worker-level covariates, such as a full set of age dummies, gender, and indicators for education and marital status. We account for the longitudinal nature of the SOEP data by including worker fixed effects (γ_i), and thus, control for unobservable, time-constant differences among workers. Additionally, we control for survey year fixed effects (τ_t) to account for possible trends in our outcomes as well as a set of federal state dummies (η_r), which are meant to capture unobservable, time-invariant differences across states that may influence individuals' health outcomes. Finally, ϵ_{ijst} represents a disturbance term. In all our specifications, we use the SOEP survey weights. Standard errors are clustered

Figure 3: Evolution of Industrial Robots in Germany, Manufacturing vs. Other Sectors (1994–2016)



Notes - This figure shows the number of robots per thousand workers in Germany separately for the manufacturing sector (left vertical axis) and other (non-manufacturing) sectors (right vertical axis) during 1994-2016. Data are drawn from the International Federation of Robotics.

at the industry level, given that we exploit the variation in robot exposure over time and across industrial sectors, rather than a measure of geographical exposure. As a robustness check, we include a Table reporting the p-values obtained using wild cluster bootstrap standard errors.

5.2 Exploiting German Tracking System

As an alternative strategy, we explore the peculiarity of tracking system to measure exposure to robots based on the occupation associated with a given vocational training path. Tracking decision in Germany occurs at the transition from primary and secondary schooling (Krause and Schüller, 2014; Zimmermann et al., 2013). Primary schools cover four grades and pupils are aged ten years when they are tracked into three different school paths: a) lower secondary school (*Hauptschule*), preparing students for manual and blue-collar professions; b) intermediate secondary school (*Realschule*), preparing students for administrative and lower white-collar jobs; and c) upper secondary school (*Gymnasium*), lasting three years longer and preparing students for higher education, allowing for direct access to universities. This decision is made jointly by parents and teachers, with teachers recommending a secondary school track to parents. This recommendation is however not binding in most states, and students are allowed to move between school tracks at any grade, although only a very small percentage (less than 2%) do so (Dustmann et al., 2017). This institutional feature of the German school system allows us to propose an alternative empirical strategy based on the tracking system and vocational training.

The SOEP includes a set of variables designed to provide information on the occupation associated with vocational training during secondary schooling (2-digit level, 99 different occupations). Since 1985, respondents are asked if they have left education since the beginning of the year before the survey and which degrees they have obtained. This information is used for the generation of the variable on the occupation associated with vocational training. Similarly, since 2001 this information is collected among respondents filling the biography questionnaire. In practice, we use the occupation associated with one's vocational training during secondary education to construct a probabilistic measure of robot exposure, which is a weighted average of the sectoral robot exposure, where the weight is given by the relative probability of working in a given sector conditional on one's vocational training path.

We restrict the sample to individuals born before 1981 to focus on those who entered a track in the early 1990s, further mitigating the concern of endogeneity concerning future robot inflows by sector.[22] Our measure of exposure to robots is then calculated as follows:

$$\text{Exposure to Robots}_{o,t}^{GE} = \sum_{j \in j} \lambda_{oj} \left(\frac{R_{j,t}^{GE}}{L_{j,1990}^{GE}} \right) \tag{8}$$

where $R_{j,t}^{GE}$ represents the stock of robots in Germany across industries in year t; and $L_{j,1990}^{GE}$ is the total number of individuals (in thousands) employed in sector j in 1990. λ_{oj} denotes the probability that an individual works in sector j given his/her initial occupation associated with vocational training. In practice, we collect information from all individuals in the SOEP with non-missing information on the occupation associated with vocational training.

This allows us to only exploit variation in robot exposure based on the track and vocational choice individuals made in school, which is unlikely to be correlated with future trends in robot adoption over time, and thus, could alleviate the concerns of selection and omitted variable bias. To conduct this approach, we include all workers reporting information on their school track and do not restrict the sample to individuals interviewed in 1994 to maximize the sample size. It is worth remarking that information on school track is only available for a sub-sample of respondents which substantially reduces our sample size. Furthermore, information on the occupation associated with vocational training is asked to a very limited sample of individuals before 2001, since the retrospective information was not collected before 2001 (SOEP, 2019). This prevents us from using work-related injuries as an alternative outcome, as this variable is available only until 1999.

5.3 Results for Germany

Panel A of Table 6 reports the OLS of the effects of robot exposure on several outcomes measuring workers' health and safety: disability, high physical burden, high psychological burden, work satisfaction, and life satisfaction. As described in the previous section, we include individual-level covariates, individual fixed effects, as well as state and year dummies in each

[22] We obtain similar results restricting the sample to individuals born before 1975, although the sample size shrinks substantially. While the effect on disability remains unchanged, the point estimate on physical burden is similar but less precisely estimated.

regression. We find that a one standard deviation increase in robot exposure is associated with a 5% reduction in the risk of reporting any disability (see column 1), and a 4% reduction in the likelihood of being employed in a highly physically intensive task (see column 2).[23] By contrast, we find no evidence of significant effects of robot exposure on mental burden (see columns 3–5).[24] Reassuringly, in Table 7 we find no evidence of significant effects when examining the impact of robot exposure between 1994 and 2000 on lagged values of disability, work accidents, and physical burden covering the 1984–1990 period, thereby providing further support to a causal interpretation of our findings.

Table 6: Effects of Robot Exposure in Germany

Dep. var.:	(1) Disability	(2) High physical burden	(3) High psychological burden	(4) Work satisfaction	(5) Life satisfaction
Panel A: OLS Estimates					
Robot exposure	-0.003**	-0.008*	-0.001	0.019	0.006
	(0.001)	(0.004)	(0.002)	(0.013)	(0.006)
Mean of dep. var.	0.064	0.210	0.187	6.897	6.931
Std. dev. of dep. var.	0.244	0.408	0.390	1.936	1.611
R-squared	0.698	0.798	0.718	0.459	0.546
Observations	64,358	63,873	63,873	63,197	64,223
Panel B: Robot Exposure based on Vocational Training					
Robot exposure	-0.015*	-0.027*	-0.011	0.369**	-0.038
	(0.008)	(0.013)	(0.014)	(0.148)	(0.121)
Mean of dep. var.	0.051	0.173	0.200	7.188	7.417
Std. dev. of dep. var.	0.220	0.379	0.400	2.032	1.612
R-squared	0.796	0.856	0.792	0.533	0.603
Observations	29,526	29,311	29,311	28,208	28,718

Notes - Data are drawn from the SOEP (1994-2016). The unit of observation is at the individual-year level. All models control for age dummies, indicators for education, marital status, state dummies, as well as year and individual fixed effects. We exclude education from the controls of Panel B because of the use of vocational training in the construction of our robot exposure measure. The sample in Panel B is restricted to individuals born before 1981. Robust standard errors are reported in parentheses and are clustered at the industry sector level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Using the measure of exposure based on the school track and vocational training and restrict-

[23]Results are only slightly larger in magnitude when excluding workers who switched their sector of employment throughout the sample studied (see Table A.19 in the Appendix).

[24]For the years before 2000, we do have information on work-injuries. When examining the effect of robot exposure on work-injuries before 2000, we find that a one standard deviation increase in robot exposure led to a 1.8 percentage point decline in the likelihood of reporting any work related injury (coeff.: -0.018; s.e.: 0.009; *p*-value: 0.06).

Table 7: Falsification Test in Germany: Robot Exposure (1994-2000) and Pre-Trends (1984-1990) in Health, Work Accidents, and Physical Burden

Dep. var.:	(1) Disability 1984-1990	(2) Work accidents 1984-1990	(3) High physical burden 1984-1990
Robot exposure (1994-2000)	0.001 (0.003)	-0.004 (0.016)	0.002 (0.008)
Observations	18,625	8,643	18,057
Mean of dep. var.	0.057	0.066	0.288
Std. dev. of dep. var.	0.231	0.249	0.453
R-squared	0.806	0.479	0.907

Notes - Data are drawn from the SOEP (1984-2016). The unit of observation is at the individual-year level. All models control for age dummies, indicators for education, martial status, state dummies, as well as year and individual fixed effects. Standard errors are reported in parentheses and are clustered at the industry sector level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

ing the sample to individuals born before 1981 (see Panel B of Table 6), qualitatively we largely confirm the findings presented in Panel A. Point estimates are larger, suggesting that an increase in one standard deviation exposure to robots reduces the likelihood of reporting any disability by 1.5 percentage points, equivalent to a 29% reduction (see column 1). Similarly, the likelihood of working in a highly physically demanding job declines by 2.7 percentage points, equivalent to a 16% reduction (see column 2). Considering the average increase in robots per 1,000 workers throughout the period studied (5.6), our results imply a 9% reduction in the likelihood of reporting any disability and a 5% decline in the likelihood of working in a highly physically demanding job. Similarly to what observed in the US, the effects on physically demanding jobs are driven by the most physically intensive occupations (see Table A.20 in the Appendix).

These larger estimates are not particularly surprising as by exploiting vocational training we focus on a sample of workers who were more likely to be exposed to robot penetration. Thus, the coefficients capture a local average treatment effect on this particular population. At the same time, we confirm the lack of negative effects on mental health (see columns 3-5), and if anything, we find evidence of a 5% increase in work satisfaction. Table A.21 in the Appendix reports the *p*-values obtained using wild cluster bootstrap standard errors for our main analysis.

We view our results as being consistent with those documented by Dauth et al. (2021), who show that robot adoption did not cause disruptive job losses with the decline in manufacturing jobs mostly driven by young labor market entrants. It is worth noting that while we focus on drug and alcohol use related deaths in the US, here, we focus on job psychological burden and self-reported metrics of mental health. We do not have information on causes of death, and unfortunately, the small sample size of our panel would not allow us to conduct this analysis using our longitudinal data.

6 Conclusion

In this study, we explore the relationship between the penetration of industrial robots and work-related injuries using data from the US and Germany. Using the US establishment-level data from OSHA, we find that a one standard deviation increase in robot exposure reduces work-related injuries by 1.2 cases per 100 full-time workers (-16% with respect to the mean; 95% CI: -1.8, -0.53). These results are driven by manufacturing firms (-1.75 injuries per 100 full-time workers; 95% CI: -2.48, -1.02), while we find no significant effects for sectors that do not adopt industrial robots (i.e., services). At the same time, areas that are more exposed to robot penetration experience higher rates of drug- or alcohol-related deaths (10.5% with respect to the mean) and mentally unhealthy days (14.9% with respect to the mean). Overall, these results are consistent with reduced physical job intensity (6.3% with respect to the mean) and increased economic uncertainty (Acemoglu and Restrepo, 2020). Employing individual-level data from Germany, we exploit within-individual variation in the exposure to robots over time and propose an alternative identification strategy exploiting information on school tracking and vocational training. We find similar results on physical job intensity and physical health but no evidence of significant effects on mental health, which appears consistent with the findings of Dauth et al. (2021), who document how the rise of new jobs in services offset the displacement effects in the manufacturing sector in Germany.

Overall, our results highlight the complex relationship between the adoption of these new technologies and the physical and mental health of workers in the sectors that are most exposed to robot adoption. Previous studies have often emphasized the negative effects robots may have on labor market outcomes. Our findings suggest that we should pay attention to the significant mental health consequences of these labor market shocks. Yet, we should not discount the potential beneficial effects of robots on workplace safety.

Future research could shed further light on how the adoption of robots affect the reallocation of tasks within firms and occupations. Understanding the complex interaction between workers and robots in the workplace goes beyond the scope of this study. The relationship between robot exposure and workers' mental health calls for a more in-depth study exploiting granular data and rich information on firms' practices and employees' well-being.

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Appendix A: Supplemental Tables

Table A.1: Descriptive Statistics in the US, 2005-2011

	Mean	Std dev
Panel A: ODI dataset - Observations: 445,562		
TCR	7.13	8.23
DART	4.19	5.43
DAFWII	2.15	3.40
Panel B: CDC Data - Observations: 4,607		
Deaths due to drug or alcohol abuse	390.6	110.8
Suicide rate	14.47	4.95
Number of mentally unhealthy days	3.71	1.38

Notes - Data are drawn from the ODI (OSHA) dataset in Panel A and from the CDC in Panel B (survey years: 2005-2011). The sample size of the suicide rate and number of mentally unhealthy days reduces to 1,379 and 4,245 observations, respectively.

Table A.2: First stage: Effects of Robot Exposure IV on Robot Exposure

	(1)
Dep. var.:	Robot exposure
Robot exposure - IV	0.423***
	(0.016)
Observations	445,562
Mean of dep. var.	0
Std. dev. of dep. var.	1

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.

*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.3: Robot Exposure, Physical and Psychological Burden - 2SLS Estimates – Alternative Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Physical burden	physical burden>median	High physical burden	Psychological burden	Psychological burden>median	High psychological burden
Robot exposure	-0.019	-0.002	-0.015***	0.013	0.005	0.004
	(0.034)	(0.006)	(0.005)	(0.028)	(0.005)	(0.005)
Observations	5,187	5,187	5,187	5,187	5,187	5,187
Mean of dep. var.	5.776	0.521	0.236	5.703	0.423	0.155
Std. dev. of dep. var.	0.402	0.0621	0.0465	0.201	0.0384	0.0218
First stage F statistic	577.2	577.2	577.2	577.2	577.2	577.2

Notes - Data are drawn from the American Community Survey (2005-2011). The unit of observation is at the commuting zone-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.

*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.4: Effects of Robot Exposure on Workplace Injuries – Analysis at the Commuting Zone-Year Level

	(1) OLS	(2) Reduced form	(3) 2SLS
	Panel A: Dep. var.: TCR		
Robot exposure	-1.544***		-1.145***
	(0.382)		(0.324)
Robot exposure - IV		-0.485***	
		(0.141)	
Mean of dep. var.	8.170	8.170	8.170
Std. dev. of dep. var.	3.341	3.341	3.341
First stage F statistic			696.5
	Panel B: Dep. var.: DART		
Robot exposure	-1.004***		-0.827***
	(0.228)		(0.207)
Robot exposure - IV		-0.351***	
		(0.088)	
Mean of dep. var.	4.535	4.535	4.535
Std. dev. of dep. var.	2.174	2.174	2.174
First stage F statistic			696.5
	Panel C: Dep. var.: DAFWII		
Robot exposure	-0.017		0.136
	(0.151)		(0.131)
Robot exposure - IV		0.057	
		(0.056)	
Mean of dep. var.	2.567	2.567	2.567
Std. dev. of dep. var.	1.613	1.613	1.613
First stage F statistic			696.5
Observations	4,480	4,480	4,480

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the commuting zone-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level. All estimates are weighted by the commuting zone-level population.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.5: Effects of Robot Exposure on Workplace Injuries - Adding State-Specific Time Trends

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: TCR			
Robot exposure	-1.575***		-1.185***
	(0.377)		(0.321)
Robot exposure - IV		-0.501***	
		(0.139)	
Mean of dep. var.	7.132	7.132	7.132
Std. dev. of dep. var.	8.235	8.235	8.235
First stage F statistic			690.5
Panel B: Dep. var.: DART			
Robot exposure	-1.013***		-0.847***
	(0.226)		(0.207)
Robot exposure - IV		-0.358***	
		(0.088)	
Mean of dep. var.	4.187	4.187	4.187
Std. dev. of dep. var.	5.429	5.429	5.429
First stage F statistic			690.5
Panel C: Dep. var.: DAFWII			
Robot exposure	-0.016		0.135
	(0.151)		(0.132)
Robot exposure - IV		0.057	
		(0.057)	
Mean of dep. var.	2.150	2.150	2.150
Std. dev. of dep. var.	3.398	3.398	3.398
First stage F statistic			690.5
Observations	445,562	445,562	445,562

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects, and state-specific time trends. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.6: Effects of Robot Exposure (Lagged by One Year) on Workplace Injuries

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: TCR			
Robot exposure $(t-1)$	-1.580***		-1.063***
	(0.362)		(0.330)
Robot exposure - IV $(t-1)$		-0.438***	
		(0.136)	
Mean of dep. var.	6.886	6.886	6.886
Std. dev. of dep. var.	8.248	8.248	8.248
First stage F statistic			470.9
Panel B: Dep. var.: DART			
Robot exposure $(t-1)$	-0.971***		-0.760***
	(0.178)		(0.201)
Robot exposure - IV $(t-1)$		-0.314***	
		(0.083)	
Mean of dep. var.	4.033	4.033	4.033
Std. dev. of dep. var.	5.406	5.406	5.406
First stage F statistic			470.9
Panel C: Dep. var.: DAFWII			
Robot exposure $(t-1)$	0.012		0.081
	(0.113)		(0.139)
Robot exposure - IV $(t-1)$		0.033	
		(0.058)	
Mean of dep. var.	2.085	2.085	2.085
Std. dev. of dep. var.	3.380	3.380	3.380
First stage F statistic			470.9
Observations	383,291	383,291	383,291

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.7: Effects of Robot Exposure on Workplace Injuries - Adding Controls

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: TCR			
Robot exposure	-1.553***		-1.163***
	(0.366)		(0.312)
Robot exposure - IV		-0.491***	
		(0.135)	
Mean of dep. var.	7.132	7.132	7.132
Std. dev. of dep. var.	8.235	8.235	8.235
First stage F statistic			692.7
Panel B: Dep. var.: DART			
Robot exposure	-1.033***		-0.865***
	(0.227)		(0.208)
Robot exposure - IV		-0.365***	
		(0.088)	
Mean of dep. var.	4.187	4.187	4.187
Std. dev. of dep. var.	5.429	5.429	5.429
First stage F statistic			692.7
Panel C: Dep. var.: DAFWII			
Robot exposure	-0.060		0.088
	(0.162)		(0.142)
Robot exposure - IV		0.037	
		(0.061)	
Mean of dep. var.	2.150	2.150	2.150
Std. dev. of dep. var.	3.398	3.398	3.398
First stage F statistic			692.7
Observations	445,562	445,562	445,562

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects, as well as commuting-zone level controls, such as the share of women, the average age and the proportion of individuals with a college degree. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.8: Effects of Robot Exposure on Workplace Injuries - Reduced Form, 1996-2011

	(1)	(2)
Dep. var.:	TCR	DART
Robot exposure - IV	-0.782***	-0.529***
	(0.076)	(0.052)
Observations	960,675	960,677
Mean of dep. var.	9.846	5.502
Std. dev. of dep. var.	17.83	14.55

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 1996-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.9: Effects of Robot Exposure on Workplace Injuries - Reduced Form, 1996-2007

	(1)	(2)
Dep. var.:	TCR	DART
Robot exposure - IV	-0.826***	-0.555***
	(0.103)	(0.089)
Observations	703,448	703,450
Mean of dep. var.	11.16	6.185
Std. dev. of dep. var.	20.03	16.62

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 1996-2007). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.10: Effects of Robot Exposure on Workplace Injuries - 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	TCR	DART	DAFWII
Panel A: Including establishment FE			
Robot exposure	-1.078***	-0.768***	0.113
	(0.413)	(0.293)	(0.216)
Observations	387,829	387,829	387,829
Mean of dep. var.	7.409	4.398	2.231
Std. dev. of dep. var.	7.953	5.490	3.425
First stage F statistic	647.7	647.7	647.7
Panel B: Sector-level robot exposure			
Robot exposure (sector-level)	-1.649**	-0.924**	-0.130
	(0.713)	(0.445)	(0.249)
Observations	360,730	360,730	360,730
Mean of dep. var.	7.625	4.554	2.284
Std. dev. of dep. var.	8.449	5.587	3.437
First stage F statistic	15.71	15.71	15.71

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. Panels A and B control for establishment fixed effects and year dummies. Standard errors are reported in parentheses and are clustered at the commuting zone level in Panel A, and IFR sector and year in Panel B.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.11: Rotemberg Weights

Sector	Rotemberg Weight
Electronics	0.78
Basic metal	0.15
Paper	0.07
Metal machinery	0.07
Construction	0.05
Automotive	0.04
Metal products	0.03
Plastic and chemicals	0.03
Glass and ceramics	0.01
Textiles	0.01
Other vehicles	0.00
Education	0.00
Mining	0.00
Food and beverages	0.00
Agriculture	0.00
Wood and furniture	0.00
Electric and gas	0.00
Other non-manufacturing	0.00
Other manufacturing	0.00

Notes - We calculated Rotemberg weights by year and sector. Here we report the average weight of each sector throughout the period of the analysis.

Table A.12: Effects of Robots Exposure on Workplace Injuries - Controlling for Trends in Low vs High Electronics Intensive Areas or Excluding Establishments in the Electronics Sector - 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	TCR	DART	DAFWII
Panel A: Controlling for Trends in the Electronics Sector			
Robot exposure	-1.212***	-0.878***	0.115
	(0.317)	(0.202)	(0.117)
Mean of dep. var.	7.132	4.187	2.150
Std. dev. of dep. var.	8.235	5.429	3.398
First stage F statistic	572.8	572.8	572.8
Observations	445,562	445,562	445,562
Panel B: Excluding Establishments in the Electronics Sector			
Robot exposure	-1.218***	-0.901***	0.116
	(0.326)	(0.211)	(0.142)
Mean of dep. var.	7.315	4.306	2.213
Std. dev. of dep. var.	8.324	5.493	3.444
First stage F statistic	703.2	703.2	703.2
Observations	424,664	424,664	424,664

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Panel A further includes specific time-trends across electronics intensive areas (below and above the median 1990 share of employment in the electronics sector). Panel B removes establishments in the electronics sector. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.13: Effects of Robots Exposure on Workplace Injuries - Controlling for Trends in Low vs High Automotive Intensive Areas or Excluding Establishments in the Automotive Sector - 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	TCR	DART	DAFWII
Panel A: Controlling for Trends in the Automotive Sector			
Robot exposure	-1.072***	-0.909***	0.011
	(0.367)	(0.254)	(0.186)
Mean of dep. var.	7.132	4.187	2.150
Std. dev. of dep. var.	8.235	5.429	3.398
First stage F statistic	298.2	298.2	298.2
Observations	445,562	445,562	445,562
Panel B: Excluding Establishments in the Automotive Sector			
Robot exposure	-1.103***	-0.801***	0.143
	(0.331)	(0.210)	(0.128)
Mean of dep. var.	7.120	4.202	2.166
Std. dev. of dep. var.	8.258	5.460	3.421
First stage F statistic	592.6	592.6	592.6
Observations	429,328	429,328	429,328

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Panel A further includes specific time-trends across automotive intensive areas (below and above the median 1990 share of employment in the automotive sector). Panel B removes establishments in the automotive sector. Standard errors are reported in parentheses and are clustered at the commuting zone level.

*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.14: Effects of Robots Exposure on Workplace Injuries - Controlling for Trade Trends and Manufacturing Trends - 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	TCR	DART	DAFWII
Panel A: Adding Controls for Trends in Trade			
Robot exposure	-1.140***	-0.863***	0.098
	(0.308)	(0.207)	(0.153)
Mean of dep. var.	7.132	4.187	2.150
Std. dev. of dep. var.	8.235	5.429	3.398
First stage F statistic	330.9	330.9	330.9
Observations	445,562	445,562	445,562
Panel B: Adding Controls for Trends in the Manufacturing Sector			
Robot exposure	-1.348***	-1.052***	0.040
	(0.310)	(0.230)	(0.171)
Mean of dep. var.	7.132	4.187	2.150
Std. dev. of dep. var.	8.235	5.429	3.398
First stage F statistic	296.3	296.3	296.3
Observations	445,562	445,562	445,562
Panel C: Including Region-Year Fixed Effects			
Robot exposure	-1.306**	-0.750**	0.344
	(0.549)	(0.373)	(0.249)
Mean of dep. var.	7.132	4.187	2.150
Std. dev. of dep. var.	8.235	5.429	3.398
First stage F statistic	566.3	566.3	566.3
Observations	445,562	445,562	445,562
Panel D: Adding Industry-Year Fixed Effects			
Robot exposure	-1.125***	-0.896***	0.116
	(0.251)	(0.189)	(0.168)
Mean of dep. var.	7.132	4.187	2.150
Std. dev. of dep. var.	8.235	5.429	3.398
First stage F statistic	341.3	341.3	341.3
Observations	445,562	445,562	445,562

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.

*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.15: Effects of Robots Exposure on Workplace Injuries - Topcoding, Logarithms and Inverse Hyperbolic Sines - 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	TCR	DART	DAFWII
Panel A: Topcoding the Outcomes at the 99th Percentile			
Robot exposure	-1.293**	-0.760**	0.274
	(0.564)	(0.368)	(0.252)
Mean of dep. var.	7.027	4.116	2.093
Std. dev. of dep. var.	6.869	4.683	2.960
First stage F statistic	566.3	566.3	566.3
Observations	445,562	445,562	445,562
Panel B: Outcomes in Logarithms			
Robot exposure	-0.125***	-0.091	0.072
	(0.048)	(0.062)	(0.065)
Mean of dep. var.	1.656	1.212	0.781
Std. dev. of dep. Var.	1.022	0.958	0.809
First stage F statistic	566.3	566.3	566.3
Observations	445,562	445,562	445,562
Panel C: Outcomes using Inverse Hyperbolic Sines			
Robot exposure	-0.143***	-0.104	0.090
	(0.055)	(0.076)	(0.083)
Mean of dep. var.	2.080	1.542	1.003
Std. dev. of dep. var.	1.251	1.199	1.031
First stage F statistic	566.3	566.3	566.3
Observations	445,562	445,562	445,562

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the establishment-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.

*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.16: Effects of Robot Exposure on Workplace Injuries, Physical and Psychological Burden, and Mental Health – 2SLS Estimates – Bootstrap P-Values

	(1)	(2)	(3)
	Panel A: Workplace Injuries		
Dep. var.:	TCR	DART	DAFWII
Robot exposure	-1.145***	-0.827***	0.136
	(0.324)	(0.207)	(0.131)
Bootstrap p-values	0.035	0.026	0.506
Observations	4,480	4,480	4,480
Mean of dep. var.	8.170	4.535	2.567
Std. dev. of dep. var.	3.341	2.174	1.613
First stage F statistic	696.5	696.5	696.5
	Panel B: Physical and Psychological Burden		
Dep. var.:	High total burden	High physical burden	High psychological burden
Robot exposure	-0.008	-0.015***	0.004
	(0.005)	(0.005)	(0.005)
Bootstrap p-values	0.110	0.006	0.385
Observations	5,187	5,187	5,187
Mean of dep. var.	0.296	0.236	0.155
Std. dev. of dep. var.	0.0436	0.0465	0.0218
First stage F statistic	577.2	577.2	577.2
	Panel C: Deaths due to Drug or Alcohol Abuse, Suicide Rate, and Mental Health		
Dep. var.:	Deaths due to drug or alcohol abuse	Deaths due to suicides	Number of mentally unhealthy days
Robot exposure	41.436***	0.339	0.555***
	(5.732)	(0.685)	(0.153)
Bootstrap p-values	0.000	0.742	0.040
Observations	4,607	1,379	4,245
Mean of dep. var.	390.6	14.47	3.713
Std. dev. of dep. var.	110.8	4.954	1.384
First stage F statistic	489.5	388	407

Notes - Data are drawn from the ODI (OSHA) dataset (survey years: 2005-2011). The unit of observation is at the commuting zone-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.17: Effects of Robot Exposure on Deaths due to Drug or Alcohol Abuse, Suicide Rate, and Mental Health – Robustness Checks – 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	Deaths due to drug or alcohol abuse	Deaths due to suicides	Number of mentally unhealthy days
Panel A: Adding Controls for Trends in the Electronics Sector			
Robot exposure	41.307***	0.290	0.548***
	(6.229)	(0.645)	(0.167)
Observations	4,607	1,379	4,245
Mean of dep. var.	390.6	14.47	3.713
Std. dev. of dep. var.	110.8	4.954	1.384
First stage F statistic	372.3	345.7	326.6
Panel B: Excluding Establishments in the Electronics Sector			
Robot exposure	40.606***	0.306	0.537***
	(6.147)	(0.662)	(0.148)
Observations	4,607	1,379	4,245
Mean of dep. var.	390.6	14.47	3.713
Std. dev. of dep. var.	110.8	4.954	1.384
First stage F statistic	357.4	321.4	313.2
Panel C: Adding Controls for Trends in Trade			
Robot exposure	42.085***	0.344	0.551***
	(5.916)	(0.687)	(0.153)
Observations	4,607	1,379	4,245
Mean of dep. var.	390.6	14.47	3.713
Std. dev. of dep. var.	110.8	4.954	1.384
First stage F statistic	479.2	381.2	402.1
Panel D: Adding Controls for Trends in the Manufacturing Sector			
Robot exposure	42.034***	0.344	0.552***
	(5.901)	(0.687)	(0.153)
Observations	4,607	1,379	4,245
Mean of dep. var.	390.6	14.47	3.713
Std. dev. of dep. var.	110.8	4.954	1.384
First stage F statistic	479.6	382.2	402.7

Notes - Data on reason of death are drawn from Vital Statistics (CDC). Data on the number of mentally unhealthy days are drawn from the BRFSS. The unit of observation is at the commuting zone-year level. All models control for commuting zone and year fixed effects. Standard errors are reported in parentheses and are clustered at the commuting zone level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.18: Descriptive Statistics in Germany, 1994-2016 - Observations: 64,358

	Mean	Std. dev.
Disability	0.064	0.244
Work accidents	0.057	0.231
High physical intensity	0.210	0.408
High psychological intensity	0.187	0.390
Work satisfaction	6.897	1.936
Life satisfaction	6.931	1.611
Age	43.937	10.134
Female	0.445	0.497
Married	0.718	0.450
Lower secondary education (basic track)	0.333	0.471
Medium secondary education (intermediate track)	0.391	0.488
Higher secondary education (academic track)	0.200	0.400

Notes - Data are drawn from the SOEP for individuals aged 18-64 years (survey years: 1994-2016). All the samples contain individuals for whom information on all observables and the respective outcome variable are not missing. The sample size of work accidents, high physical (psychological) burden, work satisfaction and life satisfaction reduces to 26,925, 63,886, 63,231 and 64,228, respectively.

Table A.19: Effects of Robot Exposure in Germany – Excluding Workers who Switched Sector

	(1)	(2)	(3)	(4)	(5)
Dep.var.:	Disability	High physical burden	High psychological burden	Work satisfaction	Life satisfaction
Robot exposure	-0.004***	-0.014***	0.001	0.037***	0.008
	(0.002)	(0.001)	(0.001)	(0.010)	(0.005)
Observations	42,129	41,843	41,843	41,458	42,032
R-squared	0.001	0.002	0.001	0.001	0.001
Mean of dep. var.	0.0622	0.195	0.193	6.935	6.969
Std. dev. of dep. var.	0.242	0.396	0.394	1.893	1.583

Notes - Data are drawn from the SOEP. The unit of observation is at the individual-year level. All models control for age dummies, indicators for education, martial status, state dummies, as well as year and individual fixed effects. Standard errors are reported in parentheses and are clustered at industry sector level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.20: Effects of Robot Exposure on Physical and Psychological Burden in Germany – Alternative Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Physical burden	Physical burden>median	High physical burden	Psychological burden	Psychological burden>median	High psychological burden
			Panel A: OLS Estimates			
Robot exposure	-0.063**	-0.011*	-0.008*	-0.100***	-0.026***	-0.001
	(0.029)	(0.006)	(0.004)	(0.014)	(0.005)	(0.002)
Mean of dep. var.	5.503	0.392	0.210	5.325	0.390	0.187
Std. dev. of dep. var.	2.902	0.488	0.408	2.947	0.488	0.390
Observations	63,873	63,873	63,873	63,873	63,873	63,873
			Panel B: Robot Exposure based on Vocational Training			
Robot exposure	-0.239**	-0.026	-0.027*	0.082	0.043*	-0.011
	(0.087)	(0.027)	(0.013)	(0.101)	(0.024)	(0.014)
Mean of dep. var.	5.480	0.378	0.173	5.368	0.394	0.200
Std. dev. of dep. var.	2.751	0.485	0.379	2.978	0.489	0.400
Observations	29,311	29,311	29,311	29,311	29,311	29,311

Notes - Data are drawn from the SOEP (1994-2016). The unit of observation is at the individual-year level. All models control for age dummies, indicators for education, marital status, state dummies, as well as year and individual fixed effects. We exclude education from the controls of Panel B because of the use of vocational training in the construction of our robot exposure measure. The sample in Panel B is restricted to individuals born before 1981. Robust standard errors are reported in parentheses and are clustered at the industry sector level.

*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.21: Effects of Robot Exposure based on Vocational Training in Germany – Bootstrap *P*-Values

	(1)	(2)	(3)	(4)	(5)
Dep. var.:	Disability	High physical burden	High psychological burden	Work satisfaction	Life satisfaction
Robot exposure	-0.015*	-0.027*	-0.011	0.369**	-0.038
	(0.008)	(0.014)	(0.018)	(0.147)	(0.104)
Bootstrap *p*-values	0.0511	0.0621	0.576	0.0210	0.735
Mean of dep. var.	0.0509	0.173	0.200	7.188	7.417
Std. dev. of dep. var.	0.220	0.379	0.400	2.032	1.612
Observations	29,526	29,311	29,311	28,208	28,718

Notes - Data are drawn from the SOEP (1994-2016). The unit of observation is at the individual-year level. All models control for age dummies, indicators for education, marital status, state dummies, as well as year and individual fixed effects. We exclude education from the controls because of the use of vocational training in the construction of our robot exposure measure. The sample is restricted to individuals born before 1981. Robust standard errors are reported in parentheses and are clustered at the industry sector level.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.