

# Immigration, Robots and the American Life<sup>\*</sup>

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## Abstract

Foreign labor represents a growing fraction of risky occupations that appear to be close substitutes of industrial robots. I investigate how dependency on immigrants interacted with robot adoption shaped a workplace injury risk in high-hazard sectors. Associating a wave of unskilled immigrants and workplace injuries across industries during 1992-2019, I find that immigrant workers substantially replaced native fatalities by crowding out natives out of risky jobs. Associated with cross-industry investment of robots, I also find that robot installation dramatically reduced injury risk, but the aggregate nationwide risk remains unabated from poor investments to riskier labor-intensive sectors (e.g., agriculture and construction). Then, I test a hypothesis that immigration inflow impeded the automation and preserved an injury risk for remaining laborers, including natives. Over-dependency on foreign labor may preserve the risky technology generating a social cost (e.g., disabilities; usage of opioids).

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# 1 Introduction

Historically, American laborers have lost their lives at their workplace. In 1900, workplace injury was 6 times more prominent cause of deaths of suicides in the U.S.<sup>1</sup> The installation of technology-embodied capitals (e.g., tractors; mining machines), however, dramatically reduced an injury risk. Since the 1990s, as a modern form of mechanization, industrial robots have increasingly operated in high-hazard sectors. (IFR (2019)) Robots presumably displace human tasks (Frey and Osborne (2017); Acemoglu and Restrepo (2017)), however, robots potentially free the workers from injury risk. If hands-off autonomous machines expectedly replace dangerous tasks, workplace injuries should be things of the history.

I start by documenting the long-run trend of injury risk in the U.S. primary and manufacturing sectors<sup>2</sup> during 1992-2019. (See Figure 1) I find that despite the continuous investment to robots, improvement of workplace safety has stalled, especially after the Great Recession. The magnitude is still concerning: both fatal and non-fatal injury risk is approximately equivalent to equivalents of traffic accidents. (See Figure 2) For some agriculture and construction occupations, non-fatal injury risk amounts to an infection rate of Covid 19. (See Appendix for injury risk by occupations) Even more underrated are non-fatal injuries as a root of public health misery, entailing social costs including medical and public insurance expenditure; The workplace injuries would also induce chronic disabilities, suppressing labor force participation<sup>3</sup>. Moreover, repetition of routinized operations would generate body pains and presumably trigger usage of pain killing drugs (i.e., Opioids)<sup>4</sup>.

One salient trend in high-hazard sectors is surging dependency on foreign labor.<sup>5</sup> As

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<sup>1</sup>In 1900, 10.2 for suicides per 100,000 people, respectively. In 1913, the Bureau of Labor Statistics documented approximately 23,000 industrial deaths among a workforce of 38 million. This corresponds to a rate of 61 deaths per 100,000 workers, approximately three times of the current suicide rate.

<sup>2</sup>The sectors account for 47% of the fatalities and 31% of non-fatal injuries in the period. Transportation is one of the riskiest sectors from traffic accidents of truck drivers, but I omit the sector for the lack of industrial robot data.

<sup>3</sup>Krueger (2017) documented that majority of non-participants have physical disabilities.

<sup>4</sup>The overdose of the pain-killing drug, opioid, is the largest increased cause of deaths in the U.S. during the new century. (See e.g. Case and Deaton (2015)) I find an extremely strong positive correlation between non-fatal injuries across states and the opioid overdose deaths across U.S. states during 2000-2019.

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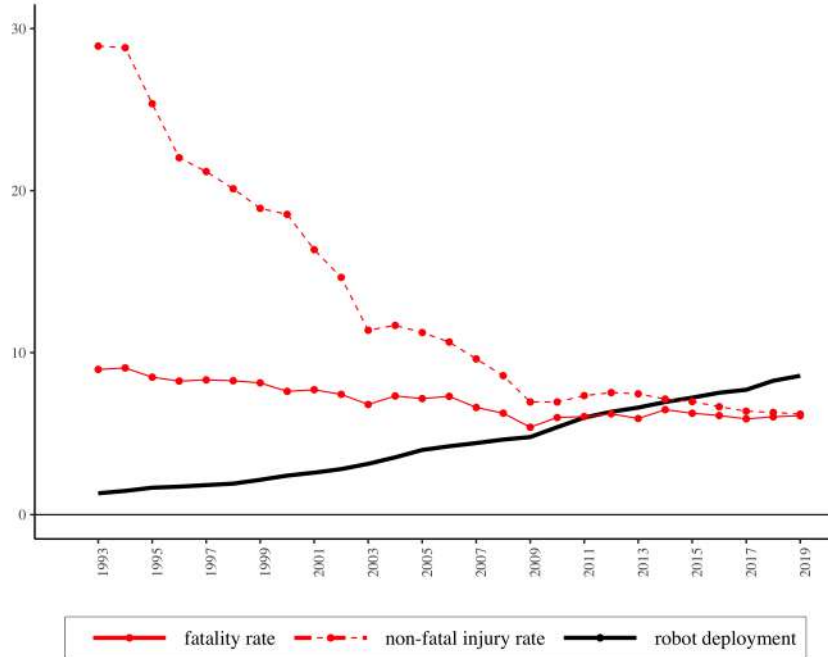


Figure 1: Aggregate trend of industrial robot deployment and workplace risk (1992-2019)

*Note:* The analysis is limited to high-hazard sectors, consisting of agriculture, construction, mining, utility and manufacturing. A fatality rate is a ratio of fatal injuries per 100,000 employment and an injury rate is a ratio of the sum of both fatal and non-fatal injuries per 1,000 employment. Fatalities are from the CFOI and non-fatal injuries are from the SOII, the employment is a 3 year moving average from the CPS. Robot deployment is units per 1,000 employments. Robots in the physical-intensive sector during 1993-2003 are extrapolated by total operating stocks of robots from the World Robotics, Industrial robots during 1993-2019.

an inflow of less educated Hispanic South Americans, including illegal ones, entered the U.S. labor market during 1990s, an employment share of immigrant surged from 8% in 1990 to 30% in 2019, with a much faster pace than in non-physical sectors. Remarkably, an immigrant share already exceeds 40% in the riskiest agriculture sector (See Figure 6).

Guided by the increased presence of foreign labor and sluggish improvement in safety in high-hazard sectors, I theoretically and empirically explore how reliance on immigrants interacted with deployment of robots affected a workplace injury risk. I pose a list of three questions. First, motivated by the puzzlingly unchanged injury risk despite the salience of industrial robots, I ask: did installation of industrial robots effectively mitigate an injury

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is one of the riskiest sectors from traffic accidents of truck drivers, but I omit the sector for the lack of industrial robot data.

risk? Second, did immigrants crowd native workers out of the risky jobs? In fact, as dependence on immigrants grows, injury cases for immigrants (or approximately Hispanics in this sector) are rising in sharp contrast to shrinkage for native injuries (See Figure 4). Third, I test a hypothesis that immigration inflow in riskier sectors impeded the automation of manual tasks. If labor supply of unskilled immigrants is abundant, employers should have fewer incentive to invest in safer technology of automation (directed technical change (Acemoglu (2002))).

To assess the inter-related associations between immigrants, robots, and injury risk described above, I assemble a balanced panel of immigration ratio computed from the Census and American Community Survey, stocks of robot in operation recovered from investment records in IFR (2019) and injury risk computed from Bureau of Labor Statistics across NAICS 4-digit industries during 1992-2019. Of course, cross-industry deployment of both robots and immigrant employment is not random. In the same vein to Graetz and Michaels (2018), I construct technologically-driven adoption of robot shocks across industries, using an instrument of an engineering feasibility across occupations developed by Frey and Osborne (2017). For identification, I assume that engineering feasibility fuels the automation adoption, but is uncorrelated to occupation risk. To address potential endogeneity of immigration inflow, I use an instrument of cross-industry historical 1950 employment share of immigrants (e.g., Ottaviano, Peri and Wright (2013))<sup>6</sup>, leveraging the immigrants tendency to agglomerate to historical ethnic enclaves of the same country of origins (Munshi (2003)), supposedly uncorrelated to current labor demands.

I report three findings. First, I estimate safety effects of industrial robots; one unit of robot reduces -1.02 fatalities out of 100,000 workers and 1.7 non-fatal injuries out of 1,000 workers. However, I find that a great majority of robot investments is installed in intrinsically safe industries (e.g., automobile; electronics) within manufacturing. Consequently, safe industries (e.g., assembling in manufacturing; moving objects in e-commerce warehouse) became increasingly capital-intensive and risky industries (e.g. cutting and welding

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<sup>6</sup>An instrument for immigration inflow to exploit the agglomeration of same ethnic group is first developed by Altonji and Card (1991) and Card (2001)) and widely used in the literature (e.g., Cortes (2008); Lewis (2011)).

in construction; sprinkling pesticides or harvesting in agriculture) remained labor-intensive in that laborers keep specialized in risky sectors. This is consistent with descriptive industry between-within decomposition of workplace injuries (Table 1), suggesting that not only within-industry, but compositional effect matters for sluggish aggregate injury risk. As a nationwide injury risk is driven by labor-intensive risky sectors armed with sizable employment shares, biased investments to automation led to sluggish improvement of the aggregate risk.

Second, at least in the short run, immigration inflow substantially replaced both a risk and level of native fatalities. Quantitatively, I find that contemporaneous 10% increase in the ratio of immigrant workers reduced fatality rate of natives by 0.27 percentage points. (i.e; 270 fatalities out of 100,000 workers) Armed with their comparative advantage in physical tasks from their lack of English proficiency (Peri and Sparber (2009)), immigrants self-selected relatively risky sectors<sup>7</sup>. I interpret that occupational sorting of natives within and between sectors occurred in response to immigrant shocks.

Third, I find that immigrants impeded the adoption of robots. The lagged estimates show that 10% increase in the ratio of immigrant workers reduces the adoption of 2.4 robots out of 1,000 workers in 5 years ahead. The finding provides an insight for poor robot investments to riskier industries (e.g., agriculture; construction); the increased labor supply of foreign labor provides economic incentives for employers to preserve the risky technology via cheaper labor costs. Their unstable short-term (or even illegal) status would allure employers to suppress labor costs from violation of minimal wage, exempted health and disability insurance coverage, immigrants' poor bargaining power and employer discrimination. Combining these findings, I conclude that puzzling stability of the national workplace risk stems from staggering automation in risky sectors, which has been impeded from heightened dependency on foreign labor.

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<sup>7</sup>Other drivers might include unfamiliarity to U.S. regional labor markets and subjective perception of injury risks.

## Literature

Due to my unified analysis on immigrants, automation and occupational safety, the paper builds on three strands of literature. Firstly, the paper contributes to classic, but currently near dormant studies on workplace injuries. The predominant concern of the literature (e.g. [Hersch \(1998\)](#); [Viscusi and Aldy \(2003\)](#)) is to estimate a compensating wage differential (CWD, below) attached to higher injury risk, initially ideated by [Smith \(1776\)](#) (See [Viscusi \(1993\)](#) for a survey of early works.) The interest of my paper is centered on how an injury risk is determined, but surprisingly little on the mechanics of workplace injuries has been addressed in labor economics.

Secondly, the paper complements with burgeoning literature on automation and industrial robots. Most of the papers, explore the automation's impact on labor market outcomes (e.g. [Frey and Osborne \(2017\)](#); [Graetz and Michaels \(2018\)](#); [Acemoglu and Restrepo \(2017\)](#); [Adachi, Kawaguchi and Saito \(2024\)](#)) Few has explored the impact on workplace safety.<sup>8</sup> The idea of immigration-induced automation is rooted in directed technical change ([Acemoglu \(2002\)](#), [Acemoglu and Restrepo \(2018\)](#)), and theoretically proposed by [Borjas \(1995\)](#), [Lewis \(2005\)](#), [Basso, Peri and Rahman \(2020\)](#), however, empirical evidence is scarce.

One notable exception is [Lewis \(2011\)](#); in the context of capital-skill complementarity, [Lewis \(2011\)](#) shows that regional entry of immigrants diminishes the a variety of autonomous machines (close to robots in this paper) across Metropolitan Statistical Area, measured by Survey of Manufacturing Technology. In the conceptual framework of automation, my analysis complements [Lewis \(2011\)](#) by more comprehensive and recent dataset from BLS.

Thirdly, the paper borrows from voluminous literature on immigration, featuring the displacement of native jobs and wage effects. (e.g., [Ottaviano and Peri \(2012\)](#); [Piyapromdee \(2017\)](#); [Monras \(2015\)](#)) Traditional concern for dependency on immigrants is whether immigrants displace native jobs. (See e.g., [Card \(2001\)](#); [Borjas \(2003\)](#)) Although the literature generally agrees on the displacement effect among less educated native workers, my paper highlights the substitution of workplace risk from occupation sorting. [Peri and Sparber](#)

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<sup>8</sup>An unpublished work of [Presidente \(2017\)](#), exploring the role of safety regulation for cross-country adoption of robots.

(2009) present a similar job reallocation mechanism to my crowding out effect where immigrants are more engaged in physical intensive sector, while natives are specialized in communication intensive sector from their comparative advantage. To the best of my knowledge, however, none has associated the immigration entry with workplace risk.

## 2 Data

I construct a panel data of workplace risk, deployment of industrial robots and immigration across industries. Guided by their salient injury risk and high presence of immigrants, I feature physically-intensive sectors (agriculture including fishing and stockbreeding, construction, mining, utility and manufacturing)<sup>9</sup>

### 2.1 Injury risk

I use workplace injury records from the U.S. Bureau of Labor Statistics (BLS). Fatal injuries are from the Census of Fatal Occupational Injury (CFOI) and non-fatal injuries, involve non-zero lost-workdays are from the Survey of Occupational Injury and Illness (SOII), respectively. Non-fatal injuries records should be considered as a lower bound, given unrecorded minor injuries. The severity of non-fatal injuries are proxied by median working days lost for recovery. The window of the analysis spans from 1992 to 2019 before the Covid crisis. Although the individual records are confidential, the BLS data query allows for disaggregate extraction for detailed unit of analysis of choice. (e.g. age×gender×industry×occupation)

An injury risk is proxied by the ratio of fatal or non-fatal injuries of full-time equivalent (40 hours × 50 weeks = 2,000 hours per year) workers. Figure 2 depicts an evolution of injury risks (both fatal and non-fatal) compared to other risks. Both fatal and non-fatal injury risk has declined from 1992, but they remained stagnant after 2008. Both are in the similar order of traffic accident risk excluding truck drivers.

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<sup>9</sup>Analogously, less educated immigration disproportionately work at manually-intensive service sectors in the U.S. (See e.g., Cortes (2008); Cortes and Tessada (2011)). I exclude these sectors, because it exhibits relatively low workplace risk and is relatively immune from the threat of automation.

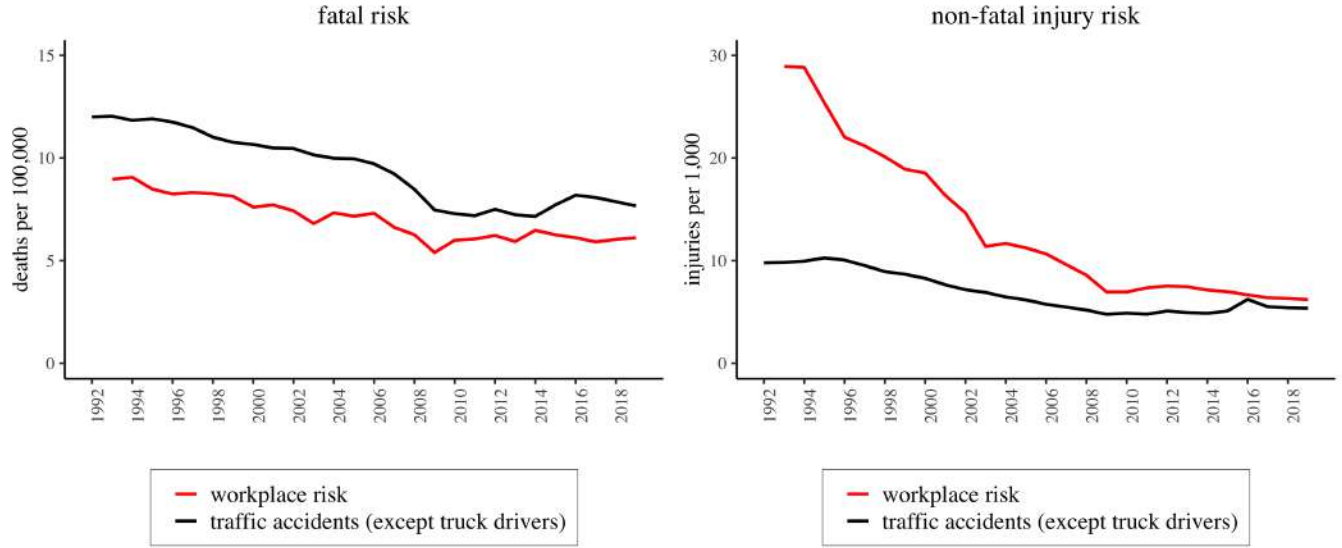


Figure 2: Long-run trend of workplace risk (1992-2019; vs. traffic accidents)

*Note:* Limited to agriculture, construction, mining and manufacturing. Non-fatal injury risks are from SOII, fatal injuries are from CFOI. Traffic accidents except truck drivers are from Fatality Analysis Reporting System, NHTSA (National Highway Traffic Safety Administration). The denominator is 3-year moving average population from CPS.

Figure 3 illustrates the trend of risks tabulated by age groups, gender and race, respectively.

Decomposing the injury risk by demographic groups (age group, gender, races and ethnicities), three points are worth noting. First, older workers are exposed to a lower non-fatal injury risk and a higher fatal risk compared to younger workers. Especially, workers with over 64 years exhibits 3 time fatal risk of workers with less than 55 ages. After the Great Recession (2008-2019), while workers above 54 year old accounts for only 6.7% of the total employment in the high-hazard sector, but 17.3% of fatalities on average. Senior workers plausibly retired or transferred to safer occupations, however, surviving seniors are under much higher fatality risk. Second, males faced a slightly higher (1992-2008) or almost comparable non-fatal injury risk with females (2009-2019; consistently with earlier period findings from [Hersch \(1998\)](#)), but a much higher fatality risk. Third, while Hispanics faced a significantly higher fatal and non-fatal injury risk than whites or blacks, suggesting that immigrants crowded out natives from risky occupations. Due to the data limit, nationality is only observed during 2011-2019. Within the sector of interest, Hispanics are proximate indicator for immigrants;

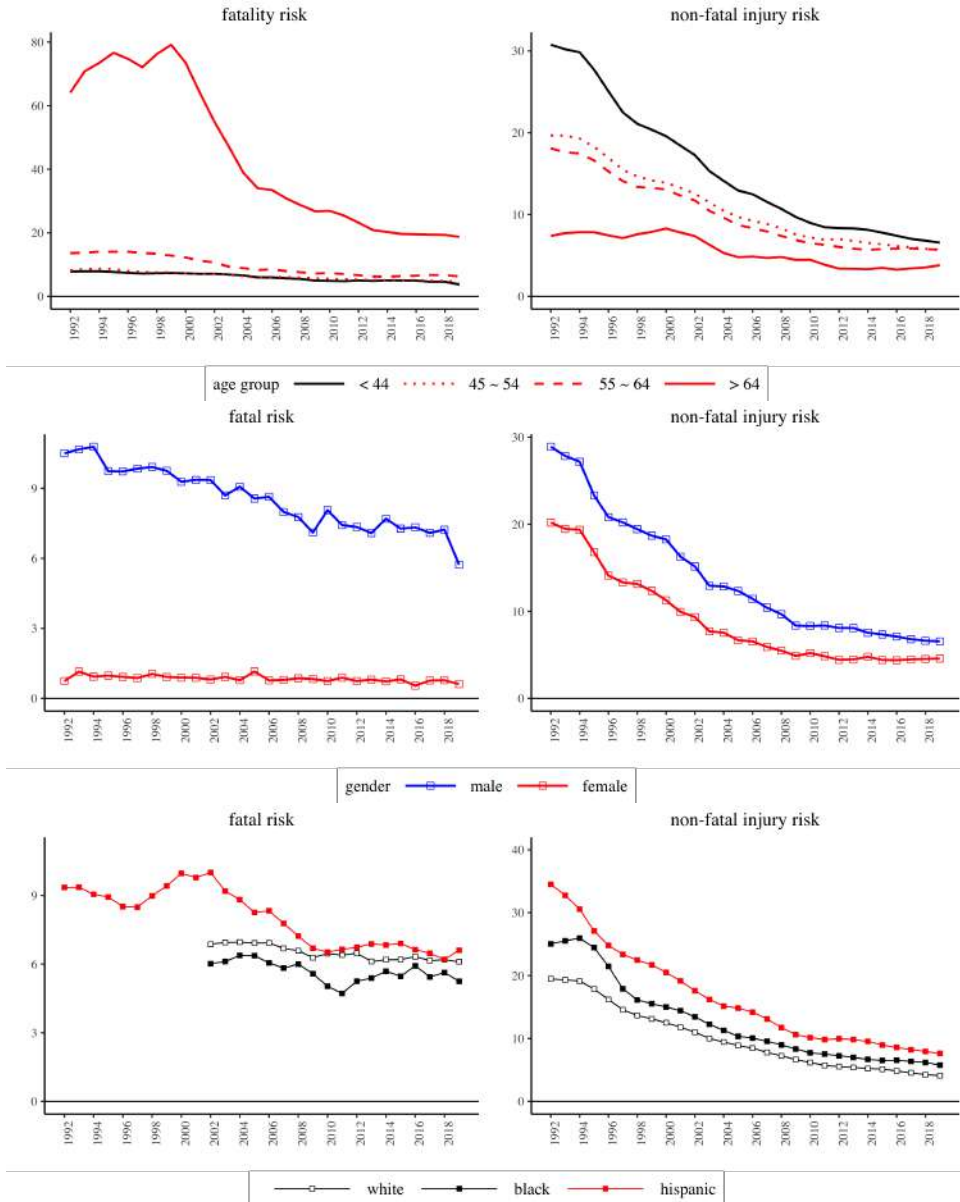


Figure 3: Injury risks across demographics (age, race and ethnicity, and gender, 1992-2019)  
*Note:* Limited to agriculture, mining, construction and manufacturing. An injury rate is a ratio of injury cases per 1,000 workers (2,000 hours equivalents, 3-year moving average from the CPS)

67% of Hispanics are immigrants and 77% of immigrants are Hispanics in 2019.

### Between-within decomposition by sectors

How does each sector contribute to the aggregate injury risk? To formerly see this, the aggregate risk is an employment-weighted average of industry-level risk such that

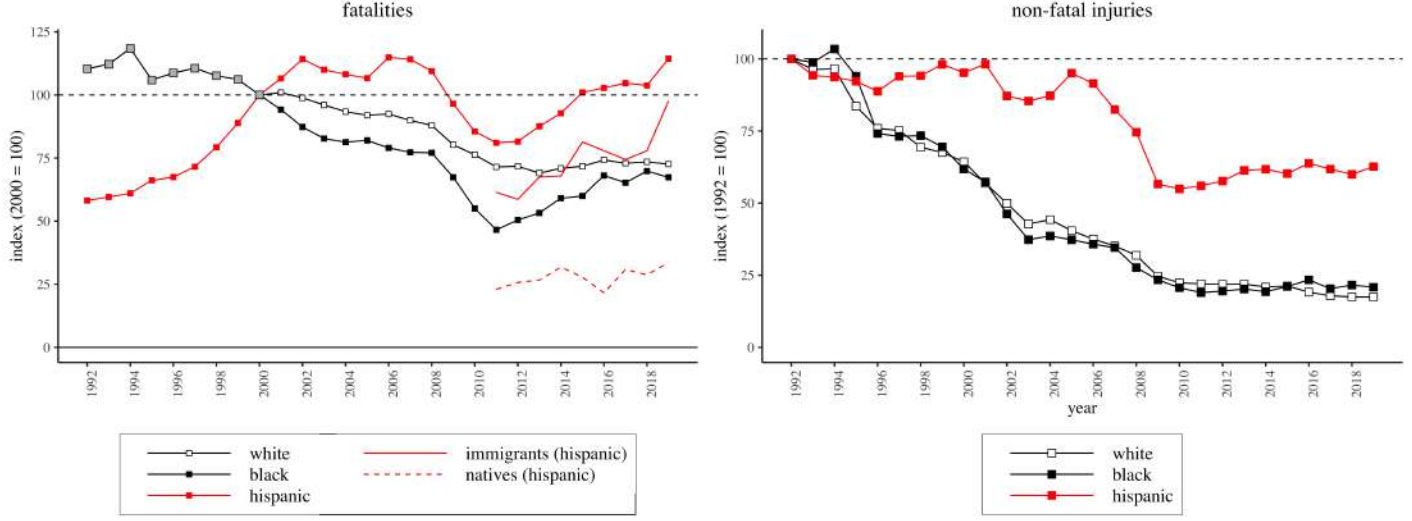


Figure 4: Injury cases of immigrants (Hispanics) vs. natives (non-Hispanic whites and blacks; 1992-2019)

*Note:* The gray line on the left is a sum of non-Hispanic whites and blacks. (A separate proxy is unavailable.) The fatalities are from CFOI and non-fatal injuries are from SOII from the Bureau of Labor Statistics. The employment hours are computed by ACS, Census, CPS. 3-year moving average.

$$r^t = \frac{I^t}{L^t} = \sum_{i \in \text{industries}} \left( \frac{L_i^t}{L^t} \right) r_i^t.$$

where  $I_i^t$  and  $r_i^t \equiv \frac{I_i^t}{L_i^t}$  is industry  $i$ 's level and risk of injuries, respectively. If the investment of robots reduce employment in the sector, even if an industrial level risk is mitigated, its contribution on the aggregate safety small due to its decreased employment weight. Differentiating w.r.t.  $\Delta t$ , one gets

$$\Delta r^t \approx \sum_{i \in I} \left( \underbrace{\frac{\Delta L_i}{L} r_i}_{\text{composition effect}} + \underbrace{\frac{L_i}{L} \Delta r_i}_{\text{safety effect}} \right). \quad (1)$$

Inside the large bracket of (1) is industry  $i$ 's contribution to the aggregate risk. The composition effect is influence from change of sectoral employment share with a risk  $r_i$  fixed. The safety effect is influence from change of risk with an employment share  $\frac{L_i}{L}$  fixed.

Table 1 documents the cross-industry contributions to the aggregate risk, before and after the Great Recession. I find that in the pre-recession era, manufacturing experienced

Table 1: Between-within sectoral decomposition of workplace risk

injury	sector	1992-2008			2008-2019			1992-2019
		composition	safety	total	composition	safety	total	aggregate
non-fatal injuries	agriculture	-0.6	-1.7	-2.3	0.2	-0.2	0.1	<b>-2.2</b>
	mining	0.4	-1.0	-0.5	0.0	-0.3	-0.3	<b>-0.9</b>
	construction	9.2	-9.1	0.1	0.1	-1.7	-1.5	<b>-1.4</b>
	manufacturing	-7.1	-20.0	-27.1	-0.2	-1.3	-1.5	<b>-28.6</b>
		1.9	-31.7	-29.8	0.1	-3.4	-3.3	<b>-33.1</b>
fatal injuries	agriculture	-0.96	-0.04	-1.00	0.92	-1.26	-0.34	<b>-1.34</b>
	mining	0.35	-0.37	-0.02	-0.06	-0.13	-0.19	<b>-0.20</b>
	construction	4.21	-2.74	1.46	0.09	1.09	1.18	<b>2.64</b>
	manufacturing	-1.04	-2.09	-3.13	-0.05	-0.12	-0.17	<b>-3.30</b>
		2.6	-5.2	-2.7	0.9	-0.4	0.5	<b>-2.2</b>

Notes: Non-fatal injury rate is cases out of 1,000 workers (SOII from BLS). Fatal injury rate is cases out of 100,000 workers (CFOI from BLS), Composition effect is change from sectoral employment share and safety effect is change from change of injury risk, as formalized in (1).

the dramatic decline in non-fatal injury risk (-20.0 out of 1,000 workers) and construction undergoes a notable decline in fatal risk (-2.74 out of 100,000 workers). In the post-recession era, improvement of safety significantly shrunk. (from -5.2 to -0.4 for fatal injuries; from -31.7 to -3.4 for non-fatal injuries) Alarmingly in construction sector, fatal risk *increased* during the period with its rising employment share. As the post-recession era, as robot investments further increased, the decomposition suggests that both compositional effect and safety effect contributes to the stability of aggregate injury risk. In particular, composition effect is more salient on fatal injuries. This motivates investigating the trend of industrial robot deployment across sectors below.

## 2.2 Industrial robots

To get a data of robots across industries, I draw on World Robotics Database by IFR (2019), offering operating stocks across industries and applications of robots, imputed from annual sales data.<sup>10</sup> IFR (2019) narrowly defines an industrial robot as “an automatically controlled, reprogrammable, and multipurpose [machine]”, excluding other types of capitals which could

<sup>10</sup>The data is widely used in literature on industrial robots, including ?, Acemoglu and Restrepo (2017) .

be labor-replacing.<sup>11</sup> Following [Graetz and Michaels \(2018\)](#), I construct an operational stock of robots using the perpetual inventory method with a depreciation rate of 10%, combining annual installations and the initial stock estimates in 2004 from [IFR \(2019\)](#).<sup>12</sup> Figure 5 illustrates the computed trend of operating stocks of robots by sector in contrast to injury risks. I note two findings. First, manufacturing sector exhibits the pre-dominant robot deploy-

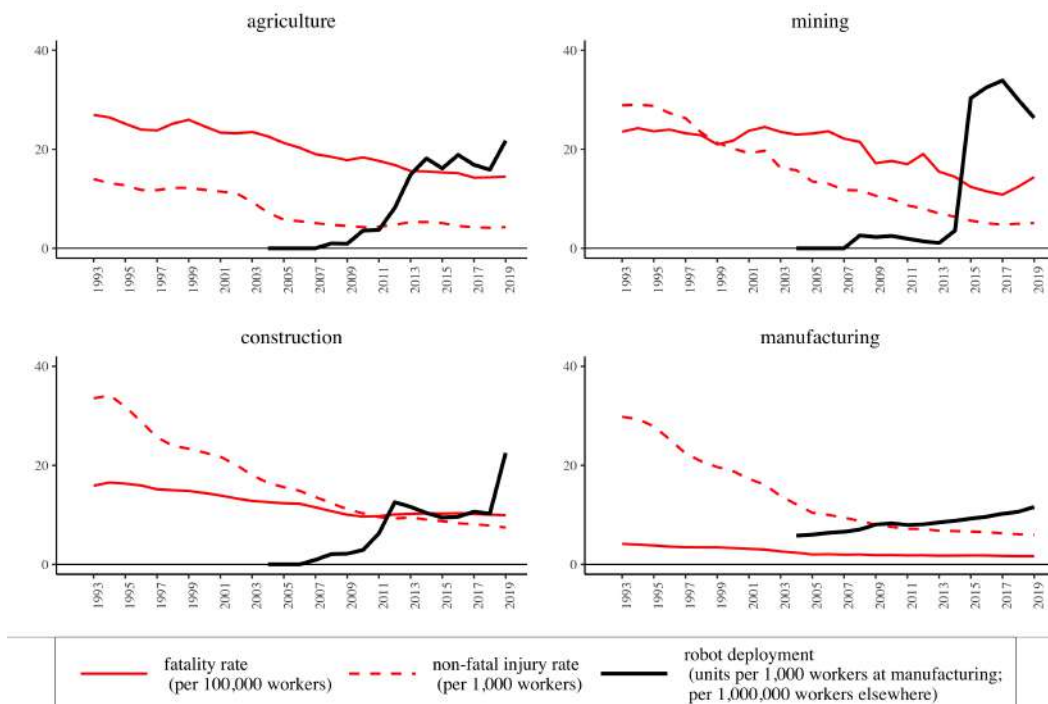


Figure 5: Robot adoption and injury rate (both fatal and non-fatal injuries) by sectors (1992-2019)

*Note:* The analysis is limited to physical-intensive sectors of agriculture, mining, construction and manufacturing. A fatality risk is a rate of fatalities per 100,000 workers. A non-fatal injury risk is a rate of non-fatal injuries per 1,000 workers. Both rates are computed from the 3-year pooled data. A robot density is units per 1,000 workers in manufacturing, and units per 100,000 workers in non-manufacturing sectors.

ment by worker by an order of  $10^3$  compared to agriculture, mining, construction. Second, investment to robots in non-manufacturing sectors are still prematurely unstable, compared to manufacturing sector. As non-manufacturing sector is riskier than manufacturing sector,

<sup>11</sup>See [Pratt \(2015\)](#) for a technological background. For example, tractors in agriculture, autonomous trucks in mining, excavator cars in construction are not counted as industrial robots.

<sup>12</sup>[IFR \(2019\)](#) documents industry-level robot stock in the U.S. only after 2004, but the assumption is that the service life of a robot is exactly twelve years with no depreciation. Using the operational stocks in [IFR \(2019\)](#) does not qualitatively change the analysis.

this also motivates the puzzle of why robots are not installed.

## 2.3 Immigration

I use the Integrated Public Use Microdata Samples ([IPUMS \(2019\)](#)) of the Current Population Survey from 1980-2018. I complement the analysis by the IPUMS of Decennial Census for the 1980, 1990, and 2000 and American Community Survey for every year from 2001 to 2015. Following [Borjas \(2003\)](#), an immigrant is defined as foreign-born non-citizen and naturalized citizens. Natives are the rest of the people in the U.S. In 1993 and before, CPS does not offer nativity or birthplace. Instead, I use a non-black and non-Asian Hispanics as an alternative. Both datasets supposedly include illegal migrants. Figure 6 illustrates the cross-industry trend of the ratio of immigrant workers in total employment.

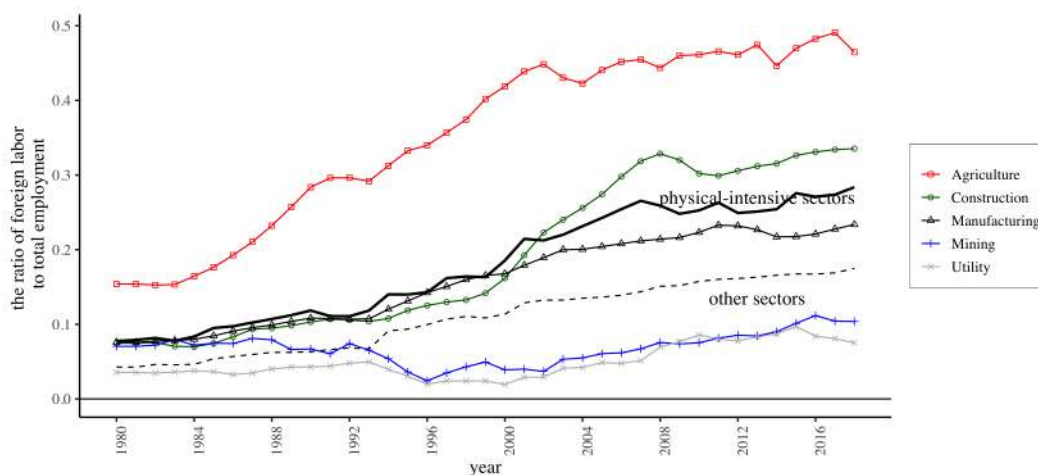


Figure 6: Dependency on foreign labor across industries in the U.S. (1980-2019)

*Note:* Computed from the Current Population Survey. The dependency is a 3 year moving average share of working hours of immigrant workers to total working hours of workers.

Table 2 is a descriptive summary of foreign vs. domestic labor working in physically-intensive sectors. The sector is predominantly occupied by full-time male workers. Immigrants exhibit two labor market disadvantages. The first is linguistic handicap. Notably, as 74% of immigrant workers are Hispanic-origin in 2015, Spanish is their predominant first language instead of English. Second, immigrants typically have lower education attainment than native workers. 44% of foreign labor drop out of high schools, compared with 9%. The disadvantages suggest comparative advantage of physical tasks relative to native workers.

Table 2: Descriptive statistics of production workers in the physically-intensive sectors

		Natives		Immigrants	
		1990	2019	1990	2019
	<b>mean age</b>	37.7	40.8	37.2	42.5
		(12.23)	(13.70)	(12.02)	(11.89)
<b>gender</b>	<b>male</b>	80.6%	86.3%	72.7%	82.1%
<b>education</b>	<b>high school dropouts</b>	0.22	0.09	0.53	0.44
	<b>high school graduates above</b>	0.50	0.58	0.28	0.38
	<b>mean schooling years</b>	0.27	0.33	0.19	0.18
		11.9	12.4	10.5	10.9
<b>race</b>	<b>White</b>	84.2%	81.0%	46.1%	53.4%
	<b>Black</b>	12.2%	11.2%	5.4%	4.7%
<b>ethnicity</b>	<b>Hispanic origin</b>	5.1%	13.6%	61.5%	77.0%
	<b>Non-English speaking country</b>	-	-	88.5%	92.2%
<b>work</b>	<b>mean wage</b>	12.0	23.1	10.2	19.1
	<b>full-time</b>	69.2%	81.9%	57.1%	79.9%
		17,512,221	11,163,229	2,377,253	3,764,331

Notes: Census in 1990 and the American Community Survey in 2017-2019 (3 year average). The production workers in agriculture, construction, mining, and manufacturing. Non-English speaking countries are countries where English is not an official language. The number of workers contain both part-time and full-time workers.

This is consistent with a crowding-out hypothesis of occupational sorting (a la Peri and Sparber (2009)).

### 3 Empirical analysis

#### 3.1 Automation and injury risk

I first infer the effect of robots adoption on workplace safety from the history of robot investments and injury risks across industries. To motivate the analysis, Figure 7 illustrates a cross-sectional link between the intensity of robot deployment and injury risk in 2019.

Both graphics show negative links, but a fatality rate shows a sharper slope (left in Figure 7). To formally test the safety effect of robots, using variations of IFR industries and years, I estimate the following equation.

$$\ln r_{i,t} = \alpha \ln R_{i,t} + \phi_i + \phi_t + \epsilon_{i,t}.$$

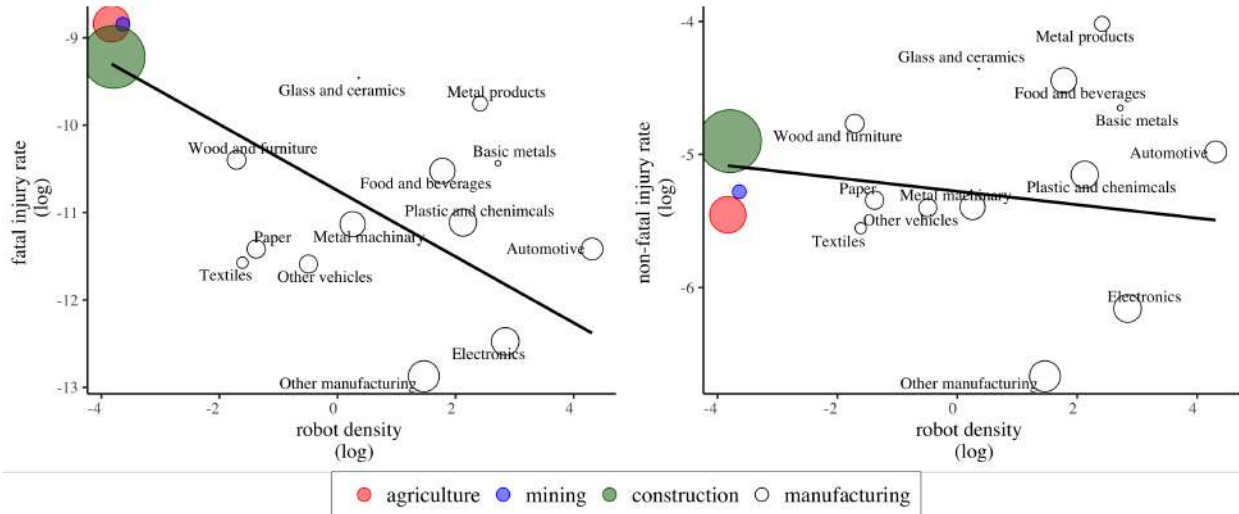


Figure 7: Cross-sectional link between robot adoption and injury risk across industries (left: fatal injury, right: non-fatal injury, 2019)

Notes: Limited to agriculture, construction, mining and manufacturing. Fatal injuries are from CFOI and Non-fatal injury risks are from SOII. Robot adoption is log of industrial robot units (?) per 1,000 workers from American Community Survey. A regression line is weighted by employment, captured by each bubble.

The outcome variables are injury risk  $r_{i,t}$ , capturing both fatal and non-fatal injuries at industry  $i$  and years  $t = \{1993, \dots, 2019\}$ .  $R_{i,t}$  is operative stock units of robots, while  $\phi_i, \phi_t$  are fixed effects of industry and years, respectively.  $\epsilon_{i,t}$  is an error term.

Fatal and non-fatal injury risk is a 3 year stacked average at year  $t, t + 1, t + 2$  ahead from the year of robot operation  $t$ , to address the small number problems and smooth out measurement errors.<sup>13</sup> After including industry and year fixed effects and controlling for industry-level demographic variables, I find a significantly negative impact of robots on injury risk as shown in (2), (4) at Table 3. Translating elasticities to units in (2) and (4), installation of a unit of robot reduces -1.02 fatalities out of 100,000 workers, and -1.7 non-fatal injuries out of 1,000 workers, respectively.

<sup>13</sup>Some industries record zero fatalities at some years. By specification, the robot investment to final two years (2018-2019) are omitted.

Table 3: Robot adoption and workplace risk across industries (2004-2015; IV estimates)

	<b>fatality rate</b>		<b>non-fatal injury rate</b>	
	<b>(log)</b>		<b>(log)</b>	
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
<b>robot density (units, log)</b>	-0.017 *** (0.002)	-0.015 *** (0.001)	-0.014 * (0.006)	-0.014 * (0.005)
<b>age (mean)</b>		0.080 *** (0.010)		-0.003 (0.029)
<b>over-64 ratio</b>		-1.97 *** (0.278)		0.260 (0.918)
<b>male ratio</b>		0.851 * (0.342)		-0.119 (0.649)
<b>immigrant ratio</b>		-0.594 (0.424)		0.075 (0.229)
<b>industry and year fixed effects</b>	Yes	Yes	Yes	Yes
<b>Adjusted R-squared</b>	0.986	0.987	0.985	0.984
<b>Observations</b>	224	224	224	224

*Notes:* Source: CPS, CFOI, SOII, and IFR (2019). The raw data for robots are available only after 2003. All models are weighted by hours of employment at the initial year, 2004. Standard errors clustered by industries are reported in parentheses. \*\*\*  $p < 1\%$ ; \*\*  $p < 5\%$ ; \*  $p < 10\%$ .

### 3.2 Immigration entry and injury risk of natives (short-run)

I ask whether immigrant workers crowded native workers from risky occupations within the sector. As a main econometric model, I estimate the following baseline equation across industries and years.

$$\ln r_{i,t}^D = \alpha \ln L_{i,t}^F + \phi_i + \phi_t + \epsilon_{i,t}.$$

where  $r_{i,t}^D$  is an injury risk for native workers. Alternatively, I use  $I_{i,t}^D$ , a level of injury of native workers as an outcome variable. Instead of  $\ln L_{i,t}^F$ , I also use an immigration ratio  $\frac{L_{i,t}^F}{\bar{L}_{i,t}}$ .  $\phi_i, \phi_t$  are fixed effects of industry and years, respectively.  $\epsilon_{i,t}$  is an error term. Table 4 summarizes results.

I find that dependency on immigrant workers significantly contributes to safety of natives, whether I use level or rate for immigrants or injuries. Evaluated at the sample mean, (2) suggests that 10% increase of immigrant employment on average reduces fatality rate of natives by 0.27 percentage point. (i.e.; 27 fatalities out of 100,000 workers).<sup>14</sup> This is con-

<sup>14</sup>Reframing as a level change, 1,000 additional inflow of immigrants reduces it by 0.1 percentage point. (e.g.; 102 fatalities of natives of 100,000 workers.)

	<b>fatal injury</b>			
	<b>(log)</b>			
	<b>level</b>	<b>rate</b>	<b>level</b>	<b>rate</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
<b>immigrant employment (log)</b>	-0.338 ***	-0.573 ***		
	(0.037)	(0.059)		
<b>immigrant share</b>			-12.3 ***	-6.34 ***
			(2.35)	(1.82)
<b>year fixed effects</b>	Yes	Yes	Yes	Yes
<b>industry fixed effects</b>	Yes	Yes	Yes	Yes
<b>Adjusted R-squared</b>	0.774	0.805	0.778	0.806
<b>Observations</b>	656	656	656	656

Table 4: Short-run impact of immigration on injury risk of natives across by industries (fatal injuries; IV estimates; 2011-2019)

*Notes:* An immigrant is a foreign-born non-citizen including naturalized citizens. An immigrant share is computed from 3 year prior pooled data from American Community Survey, while injuries are calculated from 3 year ahead pooled data from CFOI. A share of foreign labor is computed by a share of immigrant labor hours per total labor hours. \*\*\*  $p < 1\%$ ; \*\*  $p < 5\%$ ; \*  $p < 10\%$ .

sistent with a hypothesis of crowding out from occupation sorting induced from immigrants; natives transfer to safer occupations within sectors or exit to other sectors.

### 3.3 Immigration entry and robot adoption

Next, I test a hypothesis that immigration entry impedes the robot adoption. To motivate the hypothesis, I juxtapose foreign labor inflow and penetration of automation across industries in Figure 8.

Intriguingly, both graphics show significantly negative relationships. Formerly, I estimate the following basic equation across industries and years (2004-2019).

$$\frac{R_{i,t}}{L_{i,t}} = \alpha^0 \frac{L_{i,t}^F}{L_{i,t}} + \underbrace{\alpha^{-1} \frac{L_{i,t-1}^F}{L_{i,t-1}} + \dots}_{\text{lagged effects}} + \phi_i + \phi_t + \epsilon_{i,t}.$$

$\frac{R_{i,t}}{L_{i,t}}$  is a density of robots out of employment (robot units out of 1,000 workers) and  $\frac{L_{i,t}^F}{L_{i,t}}$  is a share of foreign labor at industry  $t$  and year  $t$ .  $\phi_i, \phi_t$  are fixed effects of industry and years,

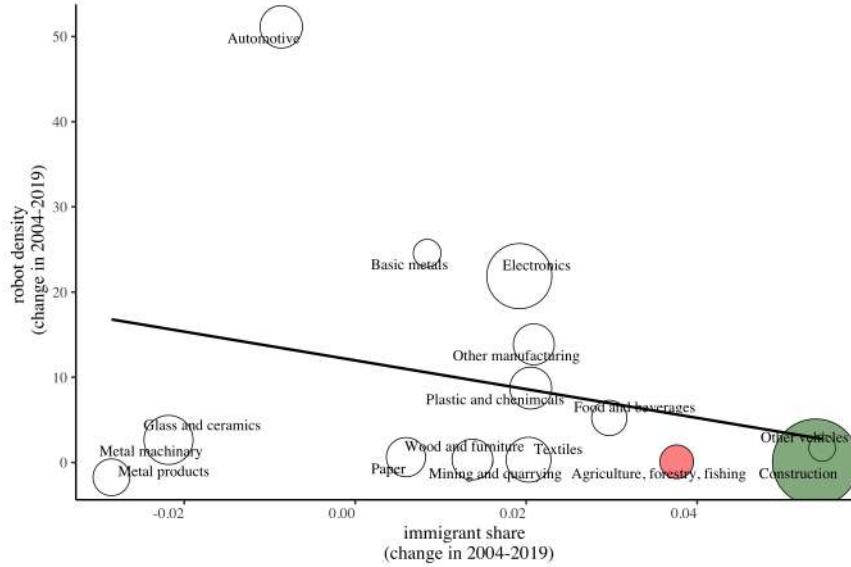


Figure 8: A share of immigrant workers and robot adoption (2004-2019)

*Notes:* An immigrant is a foreign-born non-citizen including naturalized citizens. A share of immigrant workers is computed from American Community Survey. Robot adoption is a log of industrial robot units from ? per 1,000 workers in manufacturing, mining, construction and agriculture. A regression line is weighted by an employment in 2000, captured by each bubble size.

respectively.  $\epsilon_{i,t}$  is an error term. As the response of technological adoption expectedly occur long-run, I add a series of lagged employment shares of immigrants  $\left\{ \frac{L_{i,t-1}^F}{L_{i,t-1}}, \frac{L_{i,t-2}^F}{L_{i,t-2}}, \dots \right\}$  as shown in Table 5. A contemporaneous immigrant share does not show a significant estimate in (1), suggesting that investment in robots is not reactive in the short run. Considering the lagged effects, lagged variables exhibit significantly negative estimates. (See (2) and (3)) An estimate of 5-year lag appears to be largest with strong significance. The preferred specification (3) shows that 10 percentage point increase in the ratio of immigrant workers reduces 2.4 robots out of 1,000 workers in 5 years.

Table 5: The effect of dependency on foreign labor on automation (IV estimates; 2004-2019)

	<b>robot density</b>			
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
<b>immigrant share (lag0)</b>	-0.029 *** (0.004)	-0.015 *** (0.002)	-0.017 *** (0.002)	-0.017 *** (0.001)
<b>lag1</b>		-0.034 *** (0.003)	-0.024 *** (0.002)	-0.016 ** (0.005)
<b>lag2</b>			-0.013 ** (0.004)	-0.016 ** (0.003)
<b>lag3</b>			-0.057 *** (0.009)	-0.044 *** (0.002)
<b>lag4</b>				-0.018 ** (0.006)
<b>lag5</b>				-0.028 ** (0.008)
<b>industry fixed effects</b>	Yes	Yes	Yes	Yes
<b>year fixed effects</b>	Yes	Yes	Yes	Yes
<b>Adjusted R-squared</b>	0.940	0.941	0.943	0.943
<b>Observations</b>	192	192	192	192

*Notes:* The unit of analysis is IFR industries  $\times$  years. The model is estimated during 2004-2019, weighted by employment hours in the initial period. Standard errors clustered at each sector are reported in parentheses. \*\*\*  $p < 1\%$ ; \*\*  $p < 5\%$ ; \*  $p < 10\%$ .

## 4 Conclusion

While automation accelerates in developed economies, risky jobs remain left for human workers. The paper provides a unified analysis on immigration inflow and adoption of robots and a workplace injury risk. Though the paper has been silent on normative discussions, it speaks to a nationwide selective immigration policy. In the short run, I find that dependency on immigrants saves work injuries from native workers. If the nation puts a higher premium for natives, the dependency on immigrants implies an economic benefit, albeit unethical. Moreover, since immigrants, especially, illegal ones, are not sufficiently covered by medical system or labor regulation, the country potentially saves social costs than relying on native workers. However, by suppressing employers' incentives for automating risky tasks, over-dependency on foreign labor may be alarming by preserving an old risky technology in the long run—strenuous risky workplace appears to be a hotbed for a public health crisis (e.g. spread of body pains; disability; opioid overdose) for native workers.

## References

- Acemoglu, Daron.** 2002. “Directed Technical Change.” *The Review of Economic Studies*, 69(4): 781–809.
- Acemoglu, Daron, and Pascual Restrepo.** 2017. “Robots and Jobs: Evidence from US Labor Markets.” National Bureau of Economic Research Working Paper 23285.
- Acemoglu, Daron, and Pascual Restrepo.** 2018. “Demographics and Automation.” *MIT*.
- Adachi, Daisuke, Daiji Kawaguchi, and Yukiko U Saito.** 2024. “Robots and Employment: Evidence from Japan, 1978–2017.” *Journal of Labor Economics*, 42(2): 591–634.
- Altonji, Joseph G, and David Card.** 1991. “The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives.” In *Immigration, Trade, and the Labor Market*. 201–234. University of Chicago Press.
- Basso, Gaetano, Giovanni Peri, and Ahmed S Rahman.** 2020. “Computerization and Immigration: Theory and Evidence from the United States.” *Canadian Journal of Economics/Revue canadienne d’économique*, 53(4): 1457–1494.
- Borjas, George J.** 1995. “The Economic Benefits from Immigration.” *Journal of Economic Perspectives*, 9(2): 3–22.
- Borjas, George J.** 2003. “The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market.” *The Quarterly Journal of Economics*, 118(4): 1335–1374.
- Card, David.** 2001. “Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration.” *Journal of Labor Economics*, 19(1): 22–64.
- Case, Anne, and Angus Deaton.** 2015. “Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century.” *Proceedings of the National Academy of Sciences*, 112(49): 15078–15083.

- Cortes, Patricia.** 2008. “The Effect of Low-Skilled Immigration on US Prices: Evidence from CPI Data.” *Journal of Political Economy*, 116(3): 381–422.
- Cortes, Patricia, and José Tessada.** 2011. “Low-skilled Immigration and the Labor Supply of Highly Skilled Women.” *American Economic Journal: Applied Economics*, 3(3): 88–123.
- Frey, Carl Benedikt, and Michael A Osborne.** 2017. “The Future of Employment: How Susceptible are Jobs to Computerisation?” *Technological Forecasting and Social Change*, 114: 254–280.
- Graetz, Georg, and Guy Michaels.** 2018. “Robots at Work.” *Review of Economics and Statistics*, 100(5): 753–768.
- Hersch, Joni.** 1998. “Compensating Differentials for Gender-specific Job Injury Risks.” *The American Economic Review*, 88(3): 598–607.
- IFR.** 2019. “World Robotics: Industrial Robots.”
- IPUMS.** 2019. “Integrated Public Use Microdata Series: Version 9.0 [dataset].”
- Krueger, Alan B.** 2017. “Where have All the Workers Gone? An Inquiry into the Decline of the US Labor Force Participation Rate.” *Brookings Papers on Economic Activity*, 2017(2): 1.
- Lewis, Ethan.** 2011. “Immigration, Skill Mix, and Capital Skill Complementarity.” *The Quarterly Journal of Economics*, 126(2): 1029–1069.
- Lewis, Ethan G.** 2005. “Immigration, Skill Mix, and the Choice of Technique.”
- Monras, Joan.** 2015. “Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis.”
- Munshi, Kaivan.** 2003. “Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market\*.” *The Quarterly Journal of Economics*, 118(2): 549–599.

- Ottaviano, Gianmarco IP, and Giovanni Peri.** 2012. “Rethinking the Effect of Immigration on Wages.” *Journal of the European economic association*, 10(1): 152–197.
- Ottaviano, Gianmarco IP, Giovanni Peri, and Greg C Wright.** 2013. “Immigration, Offshoring, and American Jobs.” *American Economic Review*, 103(5): 1925–59.
- Peri, Giovanni, and Chad Sparber.** 2009. “Task Specialization, Immigration, and Wages.” *American Economic Journal: Applied Economics*, 1(3): 135–169.
- Piyapromdee, Suphanit.** 2017. “The Impact of Immigration on Wages, Internal Migration and Welfare.” *mimeo*.
- Pratt, Gill A.** 2015. “Is a Cambrian Explosion Coming for Robotics?” *Journal of Economic Perspectives*, 29(3): 51–60.
- Presidente, Giorgio.** 2017. “Labor Services At Will: Regulation of Dismissal and Investment in Industrial Robots.” *mimeo*.
- Smith, Adam.** 1776. *The Wealth of Nations*. Vol. 11937.
- Viscusi, W Kip.** 1993. “The Value of Risks to Life and Health.” *Journal of Economic Literature*, 31(4): 1912–1946.
- Viscusi, W Kip, and Joseph E Aldy.** 2003. “The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World.” *Journal of Risk and Uncertainty*, 27(1): 5–76.

# Appendix

## 4.1 Aging workforce in high-hazard industries

The aging of workers in non-hispanic whites and blacks are more proceeding relative to Hispanics, especially immigrants. The fraction of workers at age over 64, whose fatality is much higher than younger workers, is increasing more for non-hispanic whites and blacks.

Younger people self-select into physical-intensive riskier industries, plausibly because physically strenuous manual tasks are plausibly better performed by younger workers with stronger physical abilities. The trend is getting weaker especially for natives.

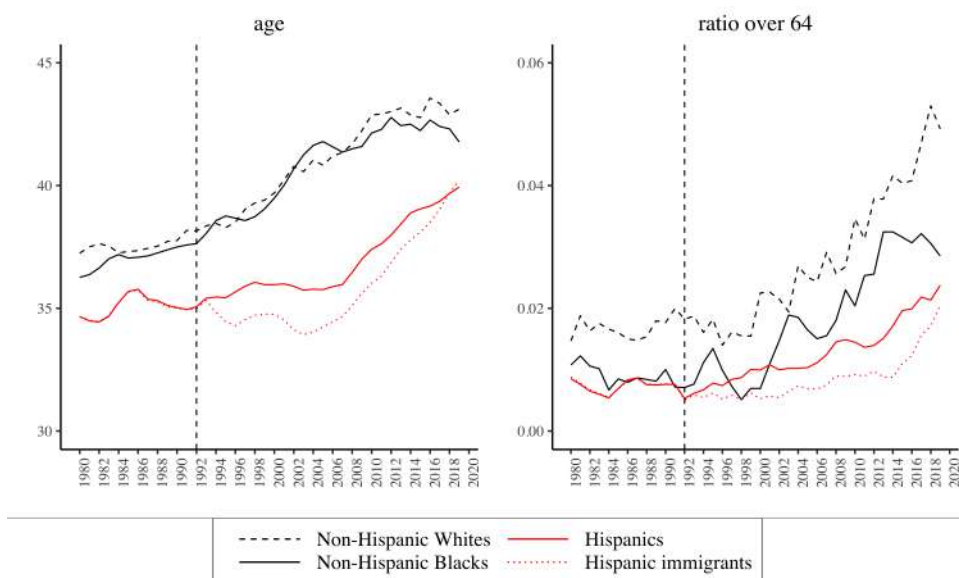


Figure 9: aging by race and ethnicity (1980-2019)

*Note:* CPS. Blacks, Hispanics and Hispanic immigrants are 3-year moving average.

## 4.2 Manual-intensity and injury risk across occupations

Occupations of stronger physical intensity are riskier. Manual-intensive occupation (with a high  $M/(C + A)$ ) has larger non-fatal injury rate across occupation.

Table 6 describes a link between manual intensity  $M/(C + A)$  of occupations and occupation risk. Manual-intensive occupations is relatively getting safer possibly due to automation. This follows Peri and Sparber (2009), calculated from ONET. Immigrants self-select to risky

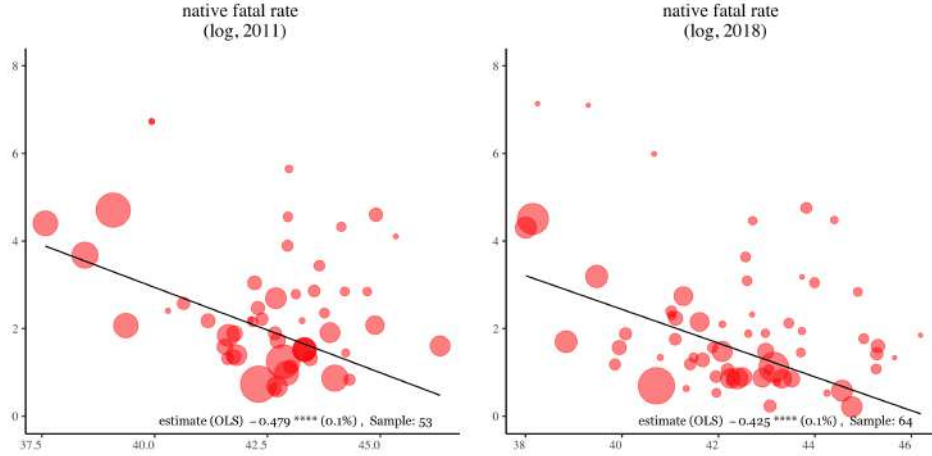


Figure 10: Aging of labor force and occupation risk by industries (2011 vs. 2018)

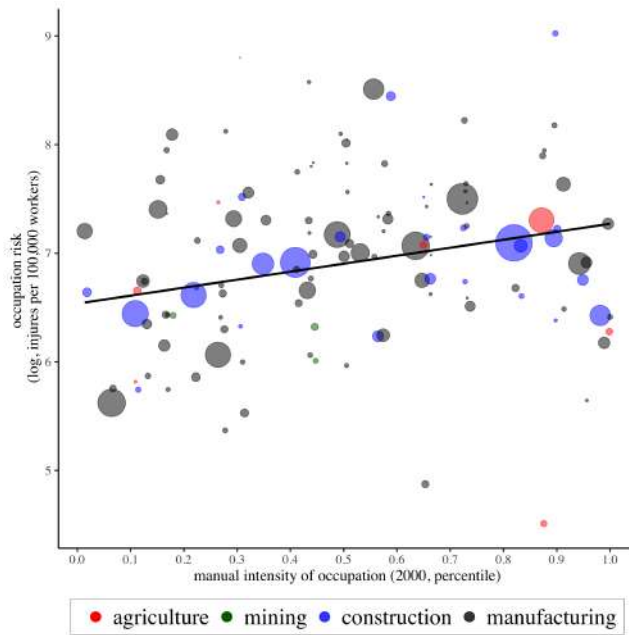


Figure 11: Riskiness across occupations of manual intensity (2019)

occupations. This pattern holds both within industries and within sectors  $\times$  industries. Especially, selection is steeper with less English proficiency are engaged in riskier occupations.

### 4.3 Immigration entry across occupations

Immigrants self-select manual-intensive occupations. (*a la* Peri and Sparber (2009)) As a result of self-selection of immigrants, the foreign dependency on manual-intensive occupations

Table 6: Manual intensity and occupation risk

	non-fatal injury rate		fatal injury rate	
	(log, per 100,000 workers)			
	(1)	(2)	(3)	(4)
<b>manual intensity</b>	0.625 ***	0.743 ***	0.284 ***	0.486 ***
	(0.101)	(0.130)	(0.105)	(0.136)
<b>manual intensity × year</b>		-0.029		-0.027 **
		(0.020)		(0.011)
<b>year fixed effects</b>	Yes	No	Yes	No
<b>Adjusted R-squared</b>	0.028	0.033	-0.002	0.009
<b>Observations</b>	1,117	1,117	1,184	1,184
	2011-2019	2011-2019	2003-2018	2003-2018

Notes: Fatalities from the CFOI, and non-fatal injuries from the SOII. Census for 1990, 2000, ACS for 2001-2018, CPS for other years. Manual intensity is at 2000.

has disproportionately risen for decades.

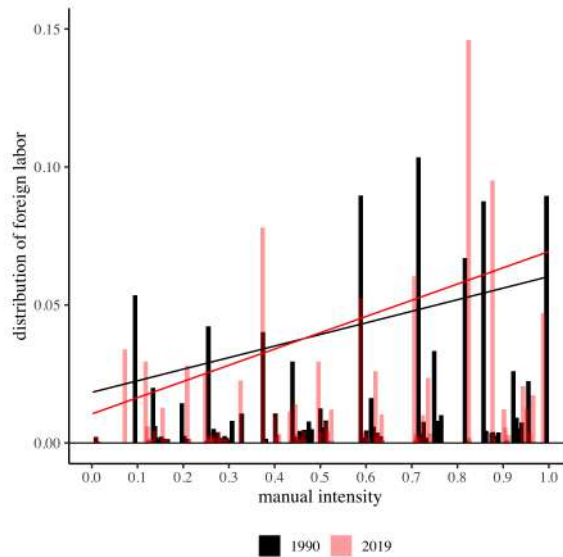


Figure 12: Distribution of foreign labor across occupations (1990 vs. 2019)

Note: Production workers in agriculture, mining, construction, manufacturing and utility from IPUMS of Census (1990) and American Community Survey (2017-2019, average). A ratio of immigrants is a ratio of working hours of immigrants out of those of total production workers. Manual intensity is computed as  $M/(C + A)$  from ONET. Regressions are weighted by working hours of each occupation.

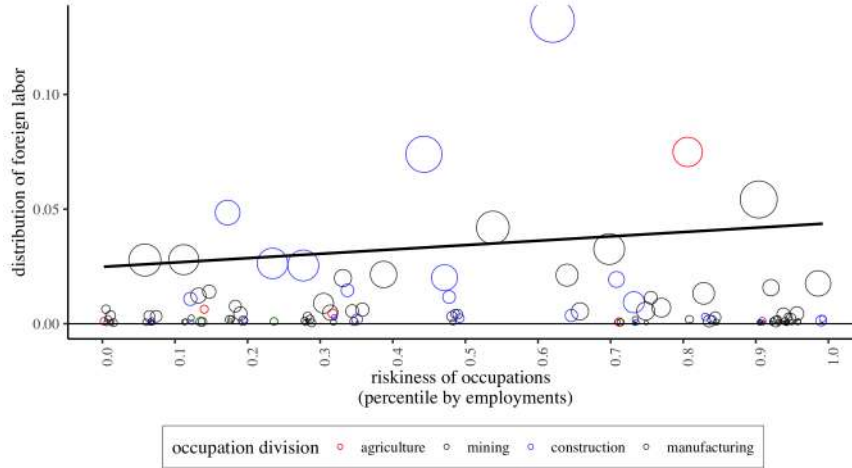


Figure 13: A distribution of foreign ratio across occupations of riskiness. (2017-2019)  
*Note:* workplace risk is fatality and non-fatal injury cases per 100,000 workers from the ACS. Industry codes (1992-2002) follows SIC and (2003-) follows NAICS.

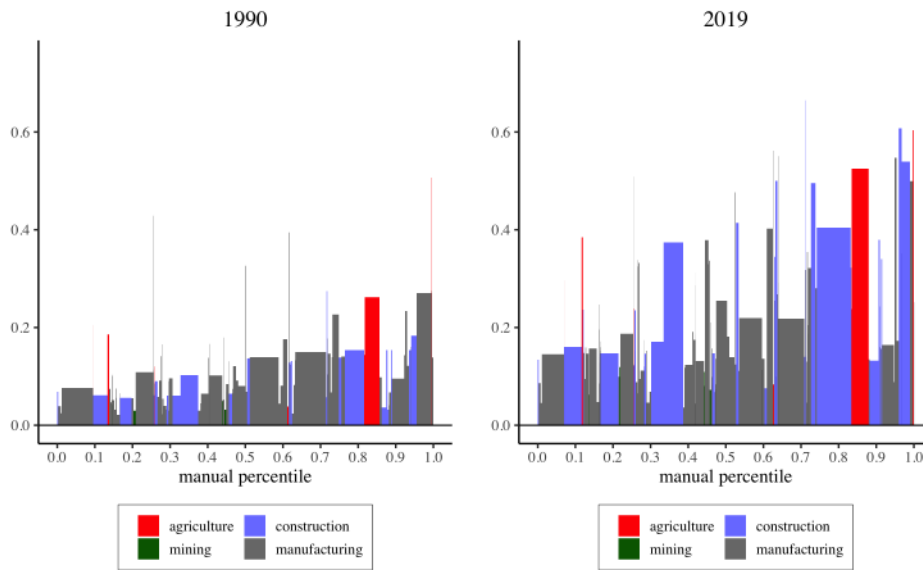


Figure 14: Foreign dependency across occupations (1992 vs. 2019)  
*Note:* Production workers in agriculture, construction, mining, manufacturing, and utility from IPUMS of Census (1990) and American Community Survey (2017-2019, average). A ratio of immigrants is a ratio of working hours of immigrants out of those of total production workers. Manual intensity is computed as  $M/(C + A)$  from ONET.

Table 7: Distribution of immigrants across the occupation spectrum

	<b>distribution of immigrants across occupations</b>	
	<b>(1)</b>	<b>(2)</b>
<b>manual intensity</b>	-0.099 *** (0.015)	-0.053 ** (0.026)
<b>manual intensity × year</b>		-0.005 ** (0.002)
<b>year fixed effects</b>	Yes	Yes
<b>Adjusted R-squared</b>	0.019	0.021
<b>Observations</b>	2,206	2,206

*Notes:* CPS during 1992-2018. Standard errors are clustered by sectoral division.