Immigration, Robots and the American Life*

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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 U.S. 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 industrial 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).

JEL Classification: D21, E22, J15, J21, J23, J31, O14, R23

Keywords: workplace injuries, immigration, industrial robots, comparative advantage

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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.[1] 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 increasingly have operated in the high-hazard sectors. (IFR (2015)) Emerging literature on industrial robots (Frey and Osborne (2017); Acemoglu and Restrepo (2017)) predict and empirically validate that robots displace human works, in contrast, robots potentially free the workers from injury risk. If hands-off autonomous machines expectedly replace dangerous tasks, workplace injuries should be eradicated.

I start by documenting the long-run trend of injury risk in the U.S. primary and manufacturing sectors[2] 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; repetition of routinized operations would generate body pains, usage of pain killing drugs (or Opioids), chronic disabilities, and would subdue male labor force participation. (Krueger (2017))[3]

One salient trend in high-hazard sectors is surging dependency on foreign labor.[4] As

[1]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.

[2]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.

[3]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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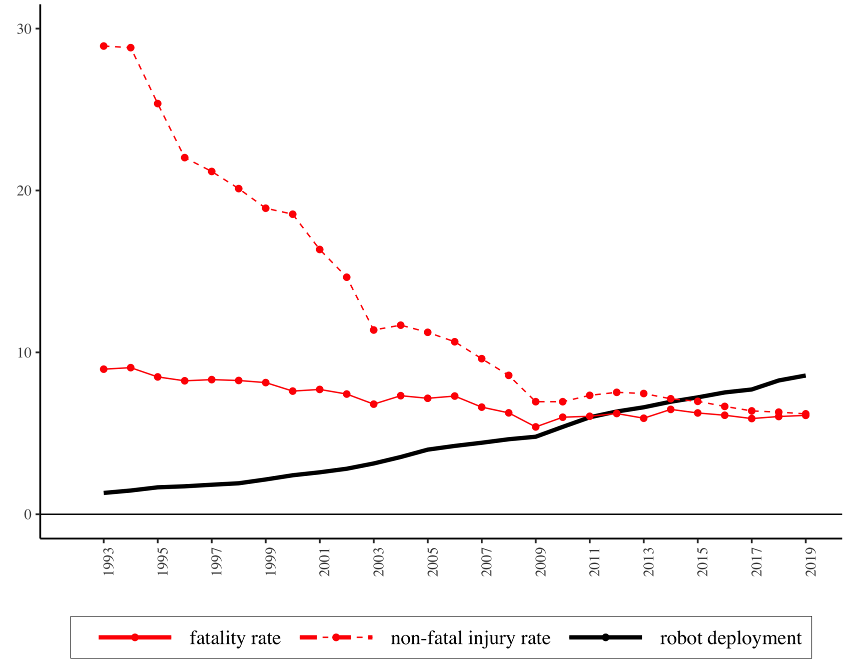

Figure 1: Aggregate trend of industrial robot deployment and workplace risk (1992-2019)
Note: The analysis is limited to high-hazard sectors, consisting of agriculture, construction, mining, utility and manufacturing. A fatality rate is a ratio of fatal injuries per 100,000 employment and an injury rate 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 de facto mitigate an injury risk?

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

Second, did immigrants crowded 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 recorded by IFR (2015) 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 (2017), I 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 address the endogeneity of immigration inflow, I use a instrument of cross-industry historical employment share of immigrants (e.g., Ottaviano, Peri and Wright (2013))[5].

I report three findings. First, I estimate safety effects of industrial robots; one unit of robot redeuces -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 Amazon warehouse) became increasingly capital-intensive and risky industries (e.g. cutting and welding in construction; sprinkling pesticides or harvesting in agriculture) remained labor-intensive. laborers keep specialized in remaining risky sectors. As aggregation of risk is heavily pulled by the sectoral labor intensity, the sectoral bias of robot investments led to the sluggish improvement of aggregate risk.

[5]The instrument to exploit the agglomeration of same ethnic group is developed by Altonji and Card (1991) and Card (2001)) and widely used in the literature (e.g., Cortes (2008); Lewis (2011)).

Second, immigration inflow substantially replaced both a ratio and level of native fatalities. Quantitatively, I find that 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, immigrants self-selected the relatively risky sector (Peri and Sparber (2009))[6]. Consequently, 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 visa status or even illegal status would potentially accelerate the shrinkage of labor costs from fewer outside options, violation of minimal wage, exempted health and disability insurance coverage, poor bargaining power and employer discrimination. Combining these findings, I conclude that the puzzling stability of the workplace risk plausibly stems from staggering investments to industrial robots to risky sectors, which has been impeded from heightened dependency on foreign labor.

Literature

Due to my unified analysis on immigrants, automation and occupational safety, the paper builds on and adds to the three strands of literature. Firstly, the paper contributes to the traditional studies on workplace injuries. (See Viscusi (1993) for a survey) The predominant concern of the literature is to estimate a compensating wage differential (CWD, below), initially ideated by Smith (1776) from micro data. (e.g. Hersch (1998); Viscusi and Aldy (2003)) They report a positive and significant CWD attached to higher injury risk. The interest of my paper differs from theirs by how the injury can be reduced by automation

[6]Other drivers might include unfamiliarity to the labor markets and subjective awareness of operation risks

technology.

Secondly, the paper complements with the burgeoning literature on automation and industrial robots. Most of the papers, explore the automation's impact on labor market opportunities (e.g. Frey and Osborne (2017); Graetz and Michaels (2017); Acemoglu and Restrepo (2017); Kawaguchi, Saito and Adachi (2019)) Few has explored the impact on workplace safety. [7]The idea of immigration affect the technology is rooted in demographic-induced 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. 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)) As mirrored by the blooming populism worldwide, 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 (2009) show the occupation sorting where immigrants are more engaged in physical intensive sector, while natives are specialized in communication intensive sector from their comparative advantage. The key mechanics of crowding out effect is close to job reallocation mechanism from comparative advantage of natives over communication-intensive tasks, presumed by Peri and Sparber (2009). To the best of my knowledge, however, none has explored the influence of immigration on workplace risk.

[7]An unpublished work of Presidente (2017), exploring the role of safety regulation for cross-country adoption of robots.

2 Data

I construct a panel data of workplace risk, deployment of industrial robots and immigration across industries. Guided by their prominent injury risk and the presence of immigrants, I set the scope of the analysis on physically-intensive sectors (agriculture including fishing and stockbreeding, construction, mining, utility and manufacturing)[8]

2.1 Injury risk

I use workplace injury records from U.S. Bureau of Labor Statistics (BLS). Fatal injuries are from the Census of Fatal Occupational Injury (CFOI) and non-fatal injuries are from the Survey of Occupational Injury and Illness (SOII), respectively. Non-fatal injuries involve non-zero lost-workdays so that minor injuries without interrupting work schedule are not included. 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$\times$gender$\times$industry$\times$occupation)

An injury risk is proxied by the ratio of injuries of full-time equivalent (40 hours $\times$ 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.

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

Decompose the injury risk by demographics, three points are worth noting on age group, gender and races.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

[8] Analogously, less educated immigration disproportionately work at a manually-intensive service sector in the U.S. (See e.g., Cortes (2008); Cortes and Tessada (2011)). I exclude this sector from the analysis, because it exhibits relatively low workplace risk and is relatively immune from the threat of automation.

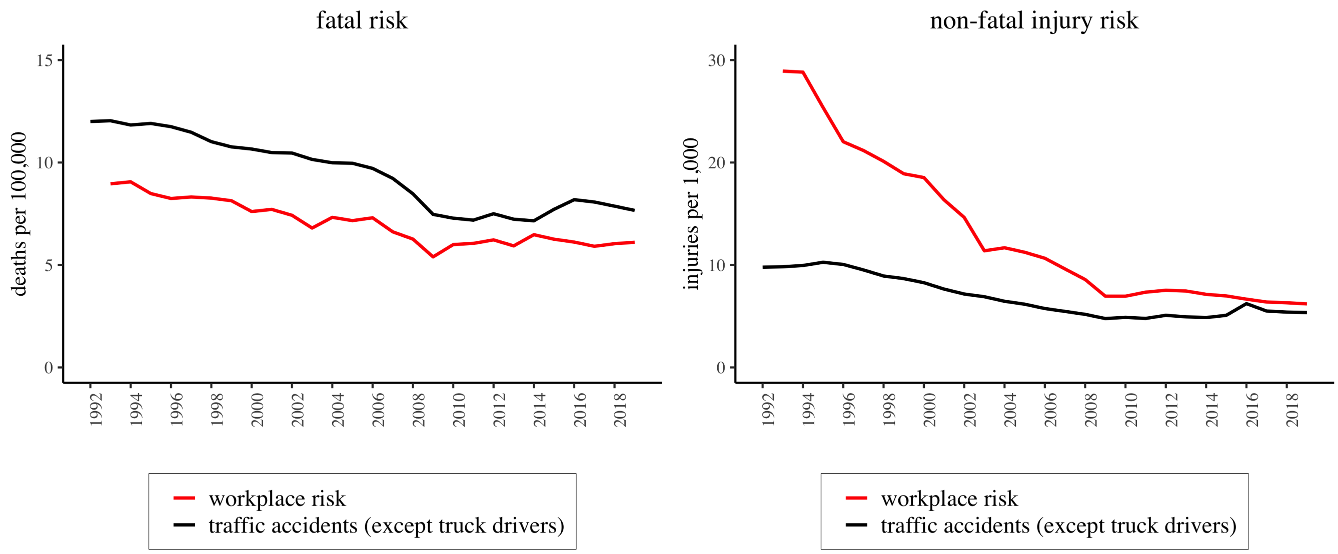

Figure 2: Long-run trend of workplace risk relative to other sources (1992-2019)
Note: Limited to agriculture, construction, mining and manufacturing. Non-fatal injury risks are from SOII, fatal injuries are from CFOI. Traffic accidents except truck drivers are from Fatality Analysis Reporting System, NHTSA (National Highway Traffic Safety Administration). The denominator is 3-year moving average population from CPS.

workers above 54 year old accounts for only 6.7% of the employment, but 17.3% of fatalities on average. Senior workers plausibly retired or transferred to safer occupations, however, surviving seniors are under much higher risk of death. 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 compared to other races. This is consistent with a hypothesis 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; 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 risks such that

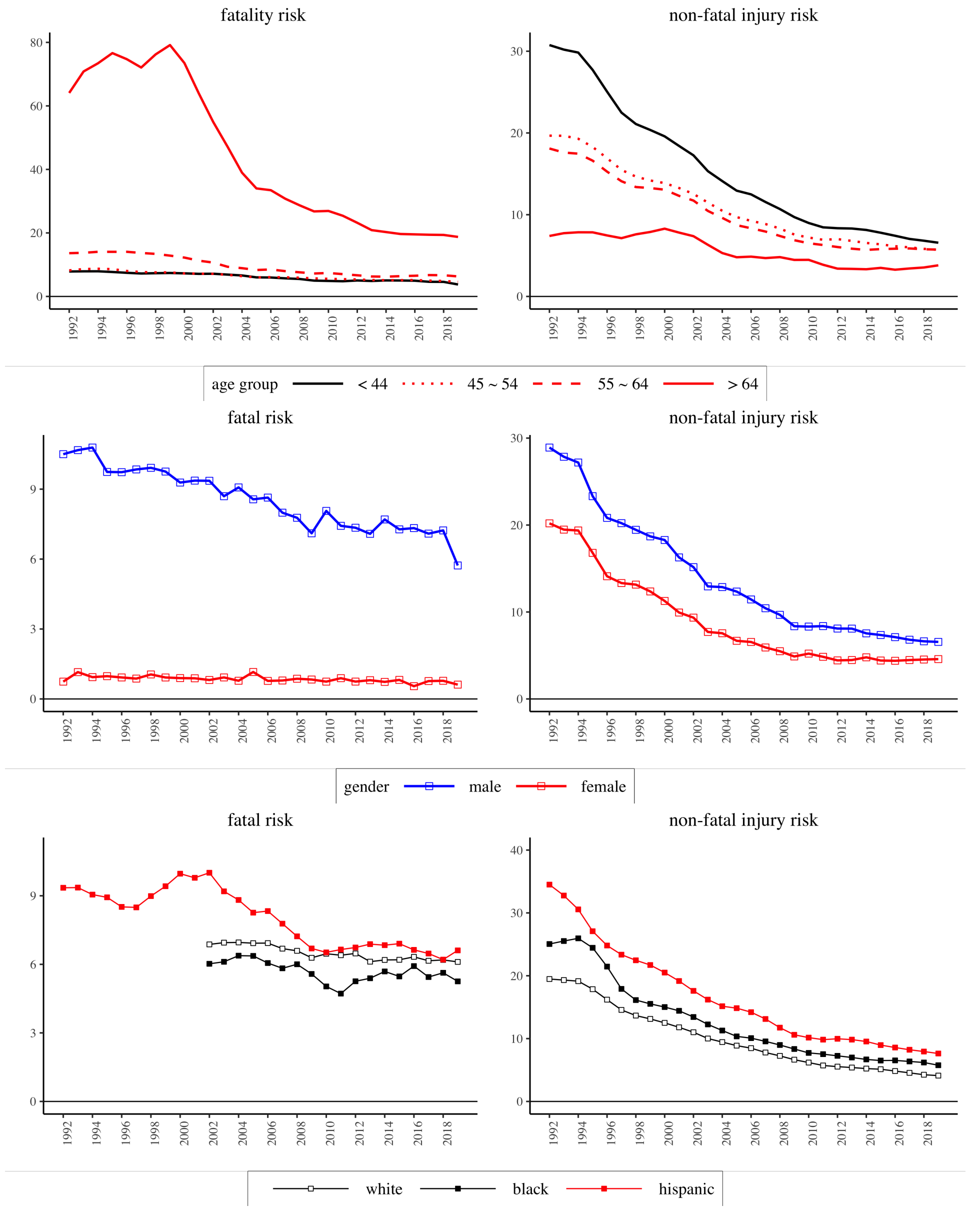

Figure 3: Injury risks across demographics (age, race and gender, 1992-2019)
Note: Limited to agriculture, mining, construction and manufacturing. An injury rate is a ratio of injury cases per 1,000 workers (2,000 hours equivalents, 3-year moving average from the CPS)

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

where $r_i^t \equiv \dfrac{I_i^t}{L_i^t}$ is industry i's injury risk. If the investment of robots reduce employment in the sector, even if an industrial level risk is mitigated, its contribution on the aggregate

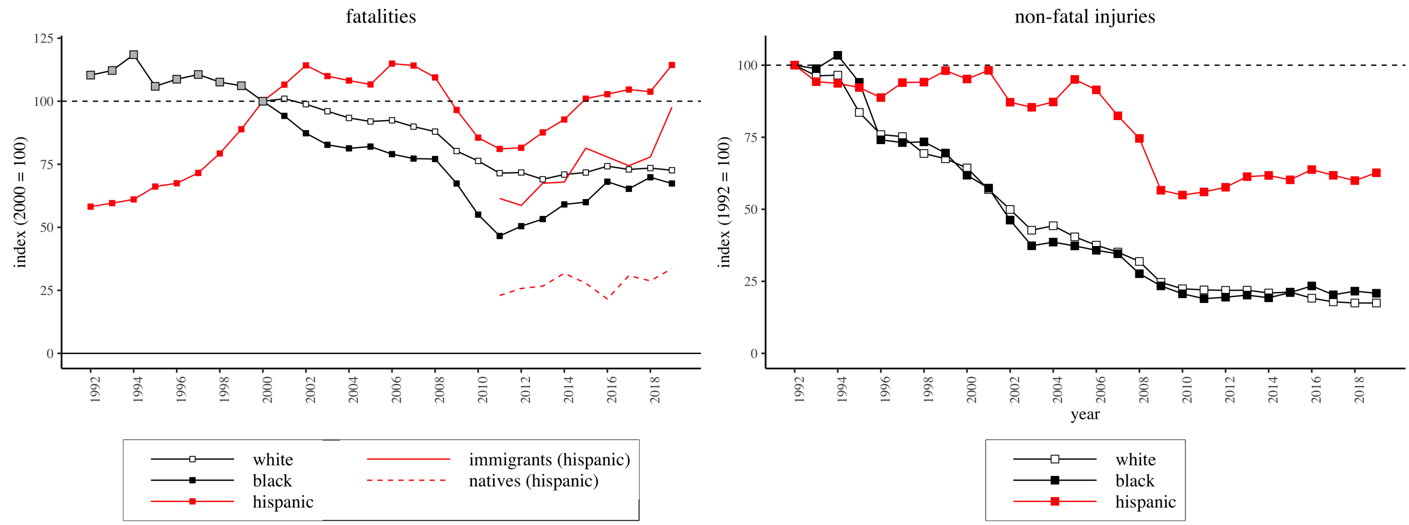

Figure 4: Injury cases of immigrants (Hispanics) vs. natives (non-Hispanic whites and blacks; 1992-2019)

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.

safety small due to its decreased employment weight. Differentiating w.r.t. Δt, one gets

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

Inside the large bracket of (1) is industry i's contribution to the aggregate risk. The composition effect is influence from change of sectoral 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 the dramatic decline in non-fatal injury risk (-20.0 out of 1,000 workers) and construction undergoes decline in fatal risk (-2.74 out of 100,000 workers). In the post-recession era, improvement of safety significantly shrinks. (from -5.2 to -0.4 for fatal injuries; from -31.7 to -3.4 for non-fatal injuries) Alarmingly in construction sector, fatal injuries *increases* during the period with its rising employment share. As the post-recession era, robot investment further increases, the decomposition suggests that the stability of aggregate injury risk is not

Table 1: Between-within sectoral decomposition of workplace risk

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

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).

by sectoral composition, but shrinking safety effect almost uniformly across sectors. This motivates us to see 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 (2015), offering operating stocks across industries and applications of robots, imputed from annual sales data.[9] IFR (2015) narrowly defines an industrial robot as *"an automatically controlled, reprogrammable, and multipurpose [machine]"*, excluding other types of capitals which could be labor-replacing.[10] Following Graetz and Michaels (2017), I construct the 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 (2015).[11] 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-

[9]The data is widely used in literature on industrial robots, including Graetz and Michaels (2017), Acemoglu and Restrepo (2017) .

[10]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.

[11]IFR (2015) 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. The analysis does not change much.

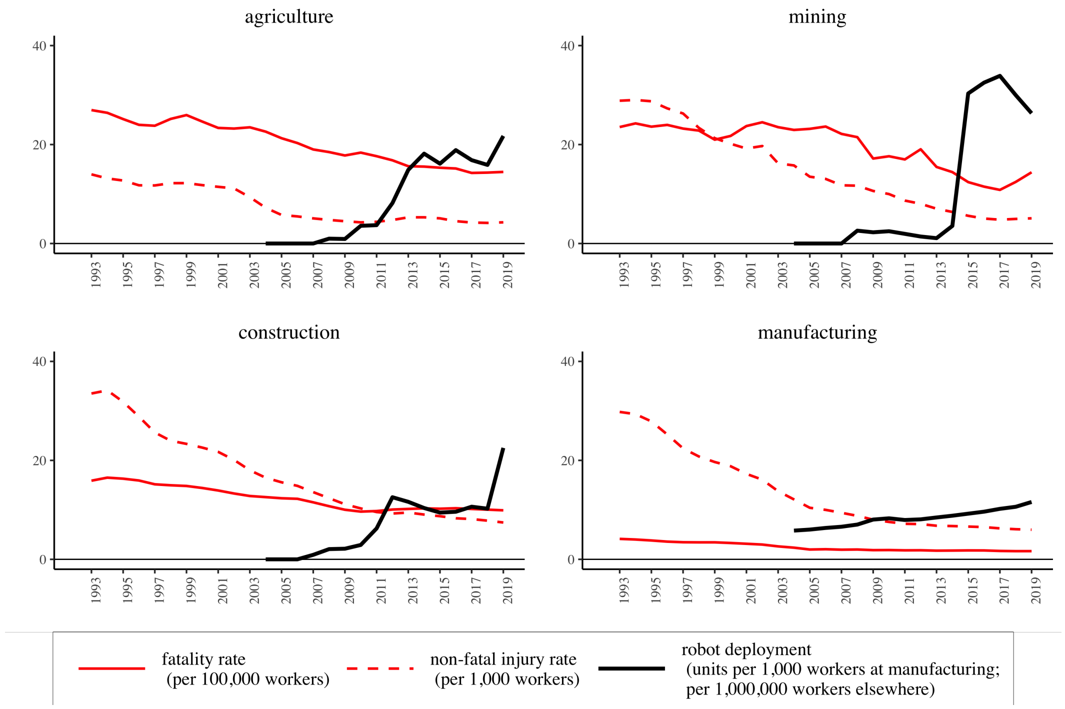

Figure 5: Robot adoption and injury rate (both fatal and non-fatal injuries) by sectors (1992-2019)

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. An 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, 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.

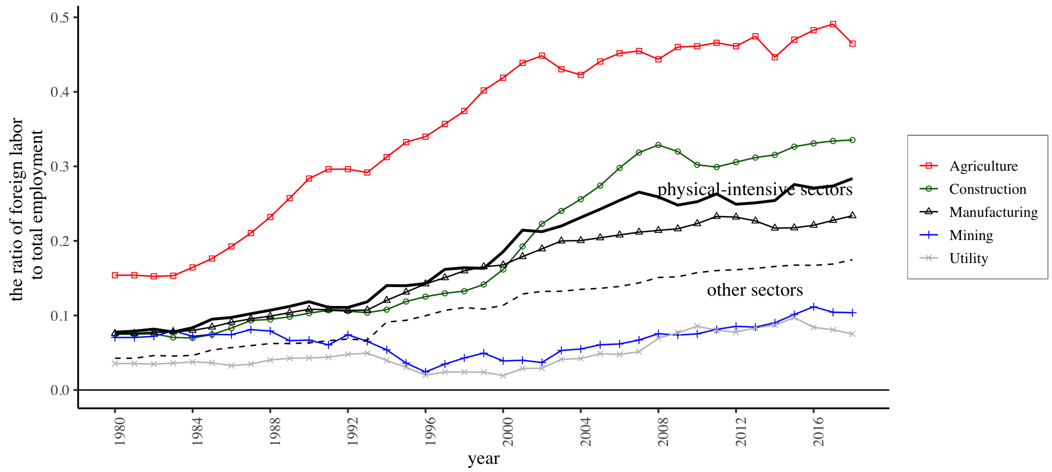

Figure 6: Dependency on foreign labor across industries in the U.S. (1980-2019)
Note: Computed from the Current Population Survey. The dependency is a 3 year moving average share of working hours of immigrant workers to total working hours of workers.

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. 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.

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

		Natives		Immigrants	
		1990	2019	1990	2019
	mean age	37.7	40.8	37.2	42.5
		(12.23)	(13.70)	(12.02)	(11.89)
gender	**male**	80.6%	86.3%	72.7%	82.1%
education	**high school dropouts**	0.22	0.09	0.53	0.44
	high school graduates	0.50	0.58	0.28	0.38
	above	0.27	0.33	0.19	0.18
	mean schooling years	11.9	12.4	10.5	10.9
race	**White**	84.2%	81.0%	46.1%	53.4%
	Black	12.2%	11.2%	5.4%	4.7%
ethnicity	**Hispanic origin**	5.1%	13.6%	61.5%	77.0%
	Non-English speaking country	-	-	88.5%	92.2%
work	**mean wage**	12.0	23.1	10.2	19.1
	full-time	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.

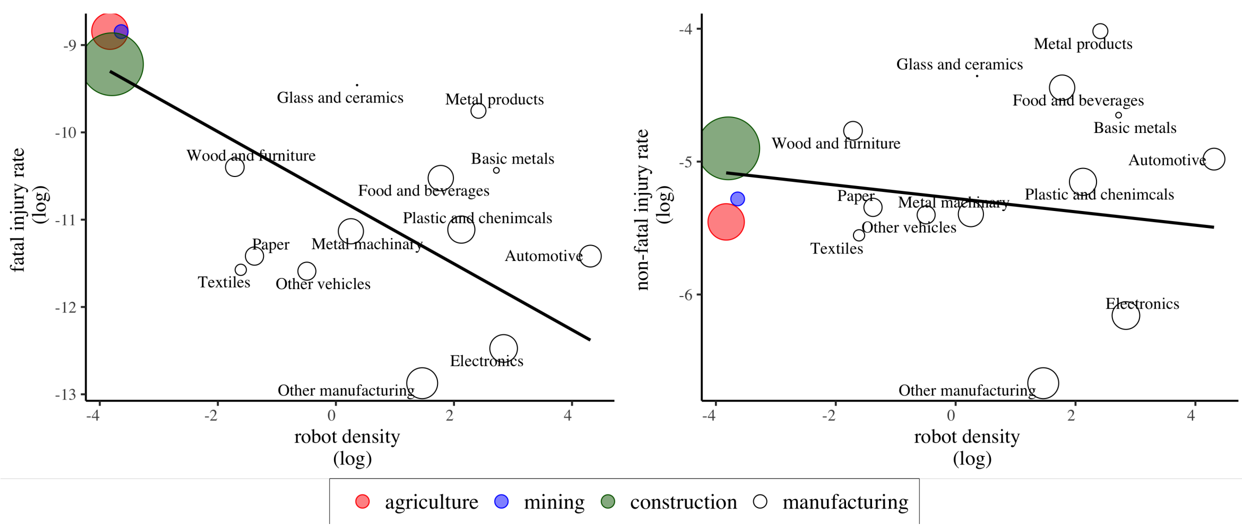

Figure 7: Cross-sectional link between robot adoption and injury risk across industries (left: fatal injury, right: non-fatal injury, 2019)

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 (IFR (2015)) per 1,000 workers from American Community Survey. A regression line is weighted by employment, captured by each bubble.

Both graphics show negative links, but a fatality rate shows a sharper slope (left in Figure7). To formerly test the safety effect of robots, using variations of IFR industries and years, I estimate the following equation.

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

The outcome variables are injury risk $r_{i,t}$, capturing both fatal and non-fatal injuries at industry i and years $t = \{1993, \cdots, 2019\}$. $R_{i,t}$ is a level of operation stocks of robots. ϕ_i, ϕ_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 average of pooled dataset (at year $t, t+1, t+2$) ahead from the year of robot level t, to address the small number problems and smooth out measurement errors.[12] 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.

3.2 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. As robots deployment at Commuting Zones is often used in the robot literature (Acemoglu and Restrepo (2020); Lerch (2020)), I also show the contrast across Commuting Zones.

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

$$\frac{R_{i,t}}{L_{i,t}} = \alpha \frac{L^F_{i,t}}{L_{i,t}} + \phi_i + \phi_t + \epsilon_{i,t}.$$

[12] Some industries include zero fatalities. By specification, the robot investment to final two years (2018-2019) are omitted.

Table 3: Robot adoption and workplace risk across industries (2004-2019)

	fatality rate		non-fatal injury rate	
	OLS			
	(1)	(2)	(3)	(4)
robot (units, log)	-0.017 ***	-0.015 ***	-0.014 *	-0.014 *
	(0.002)	(0.001)	(0.006)	(0.005)
age (mean)		0.080 ***		-0.003
		(0.010)		(0.029)
over-64 ratio		-1.970 ***		0.260
		(0.278)		(0.918)
male ratio		0.851 *		-0.119
		(0.342)		(0.649)
immigrant ratio		-0.594		0.075
		(0.424)		(0.229)
industry and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.986	0.987	0.985	0.984
Observations	224	224	224	224

Notes: All models are weighted by hours of employment at the initial period. Standard errors clustered at the sector level are reported in parentheses. The raw data for robots are available only after 2003. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

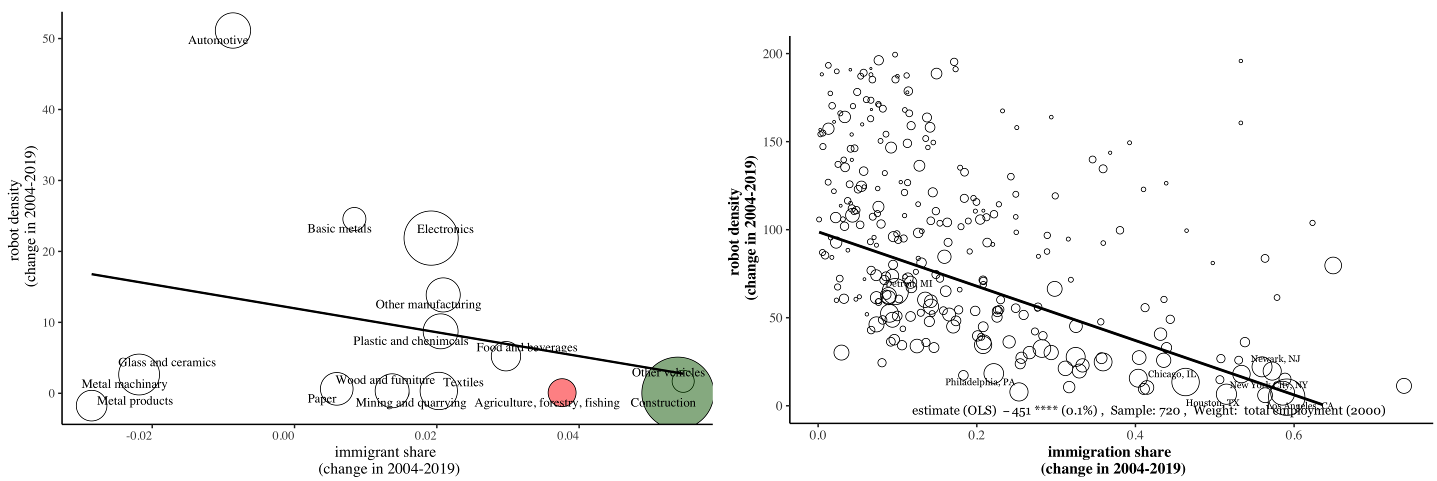

Figure 8: A share of immigrant workers and robot adoption (2004-2019, across industries (left), across Commuting Zones (right))

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 IFR (2015) 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.

$\frac{R_{i,t}}{L_{i,t}}$ is a density of robots out of employment (a unit of robots out of 1,000 workers) and $\frac{L^F_{i,t}}{L_{i,t}}$ is a share of foreign labor at industry t and year t. ϕ_i, ϕ_t are fixed effects of industry and years, 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 $\{\frac{L^F_{i,t-1}}{L_{i,t-1}}, \frac{L^F_{i,t-2}}{L_{i,t-2}}, \cdots\}$ as shown in Table 4. A contemporaneous immigrant share does not show

Table 4: Dependency on foreign labor and automation (across IFR industries)

	robot density		
	OLS		
	(1)	**(2)**	**(3)**
immigrant share (lag0)	-5.34	-15.9 **	-23.4 **
	(3.33)	(3.39)	(5.19)
lag1		7.84	11.1 **
		(5.25)	(2.21)
lag2		-10.5 **	-15.5 ***
		(2.15)	(1.99)
lag3		-17.8 ***	-8.73
		(1.83)	(5.57)
lag4		-11.5 **	-21.8 ***
		(2.65)	(1.82)
lag5		-23.6 ***	-24.4 ***
		(2.43)	(2.56)
lag6			-15.9 **
			(4.29)
lag7			-5.16
			(7.29)
lag8			-14.2 ***
			(1.78)
industry fixed effects	Yes	Yes	Yes
year fixed effects	Yes	Yes	Yes
Adjusted R-squared	0.972	0.982	0.992
Observations	256	176	128

Notes: 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

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.

3.3 Immigration entry and Workplace risk of natives

I ask whether immigrant workers crowd native workers from risky occupations within the sector. As a main econometric model, I estimate the following basic 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. ϕ_i, ϕ_t are fixed effects of industry and years, respectively. $\epsilon_{i,t}$ is an error term. Table 5 summaries a results.

	fatal injury (ma3, log)			
	level	rate	level	rate
	(1)	(2)	(3)	(4)
immigrant employment (ma3)	-0.338 **	-0.573 **		
	(0.037)	(0.059)		
immigrant share (ma3)			-12.3 **	-6.34 *
			(2.35)	(1.82)
year fixed effects	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.774	0.805	0.778	0.806
Observations	656	656	656	656

Table 5: Immigration and workplace injury of natives across by NAICS industries (fatal injuries: 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. *** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$.

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).[13] This is consistent with a hypothesis of crowding out from occupation sorting induced from immigrants; natives transfer to safer occupations within sectors or exit to other sectors.

4 Conclusion

As automation by industrial robots accelerates in developed economies, risky jobs still remain left for human workers. The paper delivers a unified analysis on immigration inflow and adoption of robots on the workplace injury, especially for native workers. Though the paper has been silent on normative discussions, it speaks to a pair of policy discussions. Though robots are sometimes debated as a new target of taxation (e.g. Anders (2020); Guerreiro, Rebelo and Teles (2017)), the subsidy for automation may be effective rather than taxation at least from the safety point of view. The study also has an implication on relaxing immigration policy to compensate for aging native workforce instead of tightening border control or deporting illegal immigrants. In the short run, I find that dependency on immigrants saves native workers from work injuries. If the nation admits a higher statistical value of life for natives than immigrants, it 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 the incentive for automation, over-dependency on foreign labor may be alarming by preserving the risky technology in the long run; strenuous risky workplace appears to be a hotbed for the public health crisis (e.g. spread of body pains and disability; opioid overdose) for native workers.

[13] 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.)

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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.

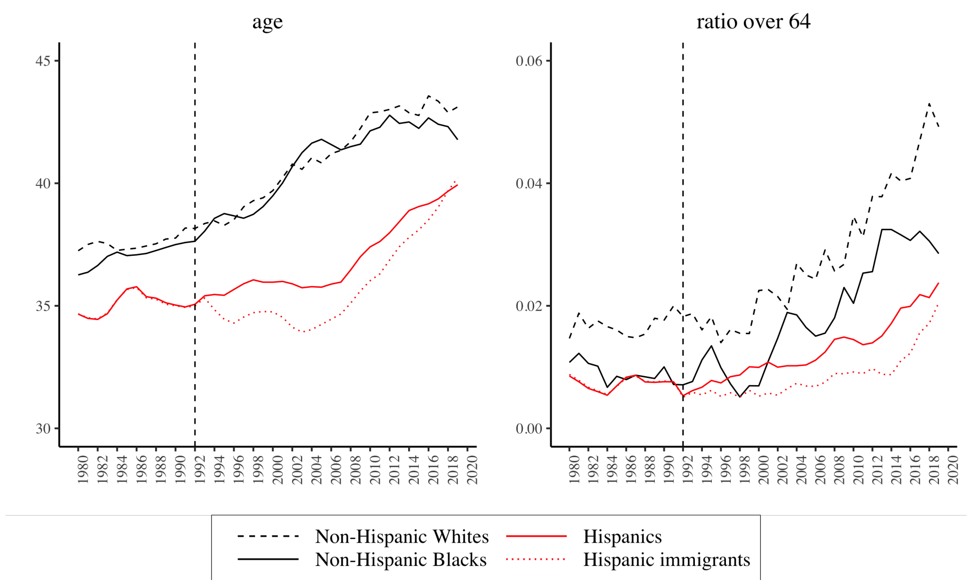

Figure 9: aging by race and ethnicity (1980-2019)

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

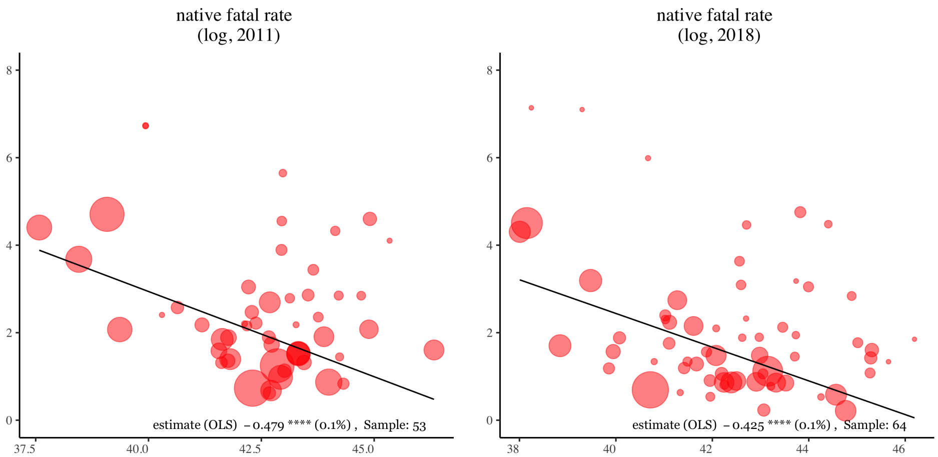

Figure 10: Aging of labor force and occupation risk by industries (2011 vs. 2018)

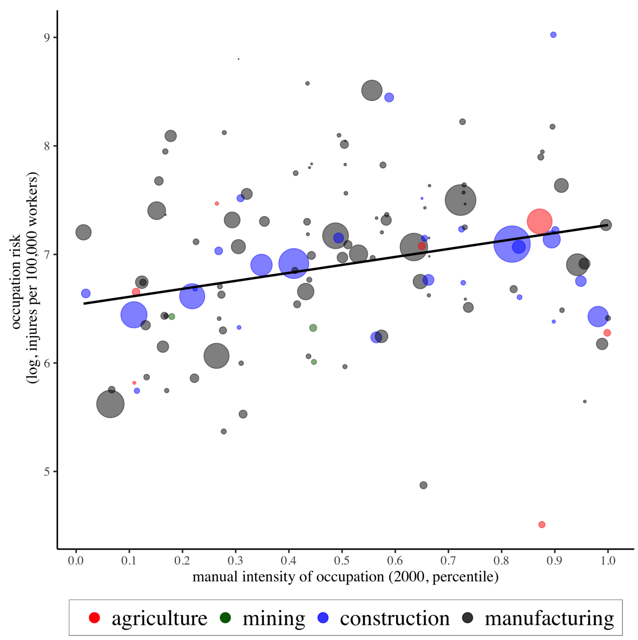

Figure 11: Riskiness across occupations of manual intensity (2019)

occupations. This pattern holds both within industries and within sectors × 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)
manual intensity	0.625 ***	0.743 ***	0.284 ***	0.486 ***
	(0.101)	(0.130)	(0.105)	(0.136)
manual intensity × year		-0.029		-0.027 **
		(0.020)		(0.011)
year fixed effects	Yes	No	Yes	No
Adjusted R-squared	0.028	0.033	-0.002	0.009
Observations	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.

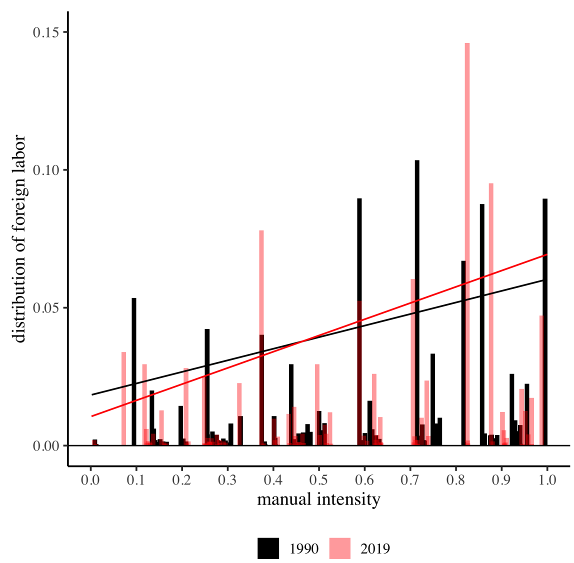

Figure 12: Distribution of foreign labor across occupations (1990 vs. 2019)

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.

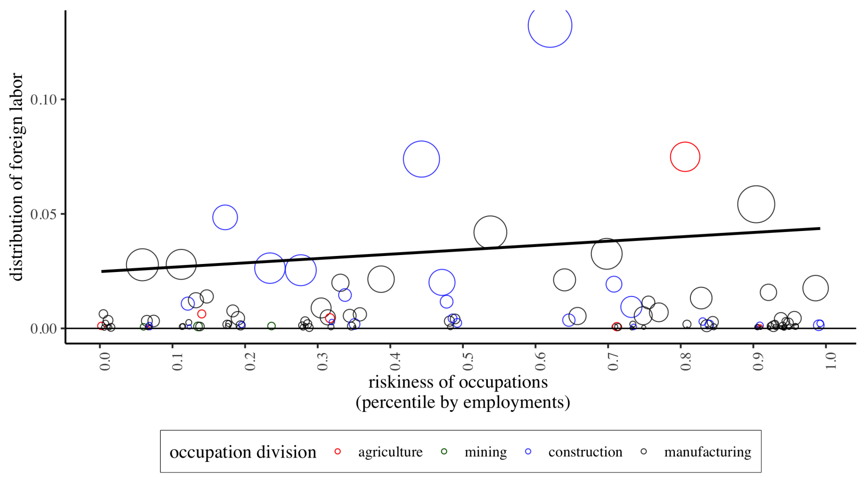

Figure 13: A distribution of foreign ratio across occupations of riskiness. (2017-2019)

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.

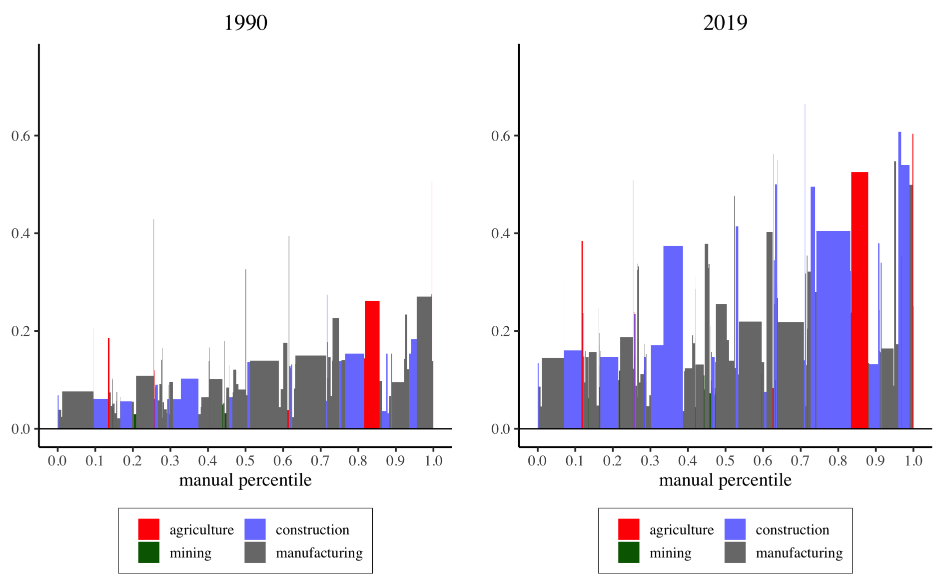

Figure 14: Foreign dependency across occupations (1992 vs. 2019)

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

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

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