September 2022

iFLAME WORKING PAPER SERIES

2022-iFLAME-05

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Import Competition and Workplace Safety in the U.S. Manufacturing Sector*

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September 2, 2022

Abstract

Relating workplace injury and illness rates to import competition in the U.S. manufacturing sector, we identify two main empirical patterns. First, industries facing more intense import competition have lower workplace injury and illness rates. Second, jobs within industries facing more intense import competition are composed of a higher proportion of safe jobs and lower proportion of dangerous jobs compared with industries facing less intense import competition.

Keywords: Workplace safety, Injuries and illnesses, OSHA, Globalization, Job displacement, Foreign competition.
JEL Classifications: F10, F61, J28.

*We thank Daniela Puzzello (Editor), the Associate Editor, four anonymous referees, Johannes van Biesebroeck, Simone Moriconi, Georg Schaur, Aloysius Siow, Luhang Wang, participants at the CUHK Conference on Trade and Development (2016) and the 2017 Asian Meeting of the Econometric Society (Hong Kong), and seminar participants at the Academia Sinica, Shanghai University of Finance and Economics, and Xiamen University (WISE) for their valuable comments. All remaining errors are our own.

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1. Introduction

The numbers of workplace injuries and illnesses in the U.S. have been declining over the past decades. According to the U.S. Bureau of Labor Statistics (BLS) the number of such cases in the private sector declined from around 6.3 million in 1991 to around 3 million in 2011, despite increased private sector employment during this period.[1] Import competition also increased during this period.[2] The literature on the relationship between the two generally shows that import competition leads to worse health according to various measures.

Focusing on the U.S. manufacturing sector, this paper builds on and extends the literature by trying to reconcile increased import competition in the sector with declines in cases of workplace injuries and illnesses. Between 1991 and 2011, the manufacturing sector observed an approximately 80% reduction in the number of such cases, compared with approximately 40% in the non-manufacturing sector.[3] However, this reduction cannot be fully explained by a similar decrease in the number of manufacturing jobs during this period, as this metric decreased by only 30–40%. Possibly, import competition led to non-uniform displacement of different types of manufacturing jobs. Import competition thus might be a contributing factor to the decrease in overall workplace injuries and illnesses in the manufacturing sector, at least to the extent that dangerous jobs were more readily displaced than safer jobs.

With this paper, we contribute to the literature by showing an association between more intense import competition and lower *rates* of workplace injuries and illnesses in manufacturing industries. By comparing data across industries and over time, our results capture the compositional changes in the industries due to import competition at both the firm and job entry-exit levels.

We also contribute to the literature by documenting evidence of the non-uniform displacement of manufacturing jobs. Consistently, studies reveal that import competition displaces jobs in the U.S., especially in the manufacturing sector. We add to this literature by documenting that dangerous jobs are more readily displaced by import competition. Such non-uniform displacement might be a channel through which import competition affects workplace injury and illness rates at the industry-level. This would be broadly consistent with the general downward trend in the workplace injuries and illnesses in the manufacturing sector.

We obtain industry-level workplace safety data from the Survey of Occupational Injuries and Illnesses (SOII) conducted by the BLS. We match workplace safety data

[1]These numbers are obtained from various issues of *the Annual Reports of Workplace Injuries and Illnesses*, published by the BLS.

[2]For example, see Figure 2 of Acemoglu et al. (2016).

[3]These numbers are also obtained from various issues of *the Annual Reports of Workplace Injuries and Illnesses*.

with the industry-level Chinese import penetration ratio. Following Autor, Dorn, and Hanson (2013) and Acemoglu et al. (2016), we address endogeneity by instrumenting this ratio with the corresponding ratios of eight other countries (Germany, Switzerland, Spain, Denmark, Finland, Japan, Australia, and New Zealand). Our identification assumptions are: U.S. industry-specific changes (e.g., changes in safety policies, unions, or worker advocacy groups) do not synchronize with corresponding changes in the other countries, and Chinese manufacturing industries do not exhibit strong increasing returns to scale. We use both a level specification, as in Lu and Ng (2013), and a long-difference specification, as in Autor, Dorn, and Hanson (2013) and Acemoglu et al. (2016). We use data from the Current Population Survey (CPS) and the NBER-CES Manufacturing Industry Database to track changes in job composition across industries and over time.

Our results show that manufacturing industries facing higher import penetration ratios have significantly lower workplace injury and illness rates than their counterparts facing lower import penetration ratios. The import penetration ratio appears to be more strongly associated with lower workplace injury and illness rates in manufacturing industries with higher fractions of production workers. Over time, the fraction of safe jobs, which tend to involve less manual and more abstract tasks, relative to dangerous jobs has increased in the manufacturing sector. We find that manufacturing industries facing higher import penetration ratios are more likely to report higher fractions of safe jobs (i.e., jobs involving more abstract tasks).

Our results complement studies examining the effects of import competition on the labor market and health in the U.S. Import competition is reported to displace U.S. jobs (Acemoglu et al. 2016, Adda and Fawaz 2020, Autor, Dorn, and Hanson 2013 and Pierce and Schott 2016), depress wages (Adda and Fawaz 2020 and Autor, Dorn, and Hanson 2013),[4] and increase the use of non-routine skills, including interpersonal, cognitive, and manual skills, and reduce the use of routine skills in manufacturing industries (Lu and Ng 2013). These effects, however, may be non-uniform across jobs and regions. For instance, Bloom et al. (2019) show that import competition displaces jobs in the manufacturing sector but increases those in the service sector in areas with high human capital and in large firms; such competition also leads to geographic job reallocation from inland to coastal areas. Adda and Fawaz (2020) find that in regions with higher proportions of jobs involving routine tasks, import competition discourages labor market participation and depresses household incomes. These authors also document an increase in both hospital admission rates among residents and mortality rates among manufacturing workers in those regions. Their results reinforce those of Pierce and Schott (2020) and Lang, McManus, and Schaur (2019),

[4]Similar job displacement effects are found in Denmark and Mexico (Utar 2014, 2018 and Utar and Ruiz 2013).

who observe increases in deaths and a general worsening of health conditions among residents in U.S. counties more exposed to import competition relative to less-exposed counties.

Our results complement those of Bloom et al. (2019) and Lu and Ng (2013) by showing non-uniform trade-induced job and task displacement within the manufacturing sector. Specifically, we observe more rapid displacement of dangerous jobs. We also observe that trade increases the relative importance of abstract tasks. When different jobs and tasks are displaced non-uniformly because of import competition, firms might also be displaced non-uniformly. In Appendix A, we decompose the aggregate safety trends in the American workplace and find that a large proportion of safety improvements happen within rather than between sectors, and that variations are particularly pronounced across industries. We are thus motivated to set our unit of analysis at the industry level that would encompass within-industry changes in the composition of firms and jobs that are induced by import competition. Our industry-level results therefore do not contradict with McManus and Schaur (2016), who find that import competition increases workplace injury rates among small establishments but not large establishments.

We describe our data in detail in Section 2. In Section 3, we lay out our specifications and discuss our identification strategy and other potential issues with estimation. In Section 4, we present our results and discuss the economic significance. In Section 5, we look more closely at compositional changes in the manufacturing sector over time by job type. We conclude the paper in Section 6.

2. Data

2.1 Injury and illness rates

In our empirical analysis, we use the injury and illness rates from the public version of the Survey of Occupational Injuries and Illnesses (SOII) provided by the BLS.

The Occupational Safety and Health Act of 1970 (29 U.S.C. 651), which is enforced by the Occupational Safety and Health Administration (OSHA), requires nonexempt employers to prepare and maintain records of injuries and illnesses in their workplaces.[5] According to the Code of Federal Regulations (Title 29, Subtitle B, Chapter XVII, Part 1904), "an injury or illness is an abnormal condition or disorder. Injuries include cases such as, but not limited to, a cut, fracture, sprain, or amputation. Illnesses include both acute and chronic illnesses, such as, but not

[5] Employers with 10 or fewer employees are exempted. Worksites in specific low-hazard industries such as retail, service, finance, insurance, and real estate, are also exempted.

limited to, a skin disease, respiratory disorder, or poisoning."[6] Employers must display a summary of their records in their workplaces' common areas, where they are visible to employees.[7]

The BLS records workplace injuries and illnesses at the establishment level through its SOII. These records contain the names, addresses, industries, and injury and illness rates of the participating establishments. An establishment differs from a firm. Fort, Pierce, and Schott (2018) emphasize that manufacturing firms are increasingly engaging in non-manufacturing activities, as shown by the increasing number of non-manufacturing establishments in recent decades. The SOII data alleviate this concern by targeting manufacturing establishments but not manufacturing firms. The establishment-level SOII data are not publicly accessible. Instead, BLS makes available annual summaries of these data at the industry-level in the form of the *Survey of Occupational Injuries and Illnesses — Annual Summary* (SOII-AS).

The SOII data are used in the occupational health literature. Data are available from 1972 to the present. In aggregating the establishment-level data to produce industry-level summaries, the BLS uses weighting to ensure the representativeness of these data. The disclosure rules imposed on these industry-level data render many 4-digit figures unavailable.[8] Unpublished industries are only included in the total of the upper levels. For instance, although the estimated injury rate of a 4-digit SIC industry is not published, its injury rate is included in the injury rate of the respective 3-digit SIC industry.

In our baseline analysis, we mainly use 3-digit SOII-AS data because of the relatively high attrition rate of the 4-digit data.[9] We use 3-digit data to construct the injury and illness rate, R_{jt}, for industry j in year t as follows:

$$\begin{aligned}\text{Injury and illness rate} &= \frac{\text{Number of injury and illness cases} \times 100}{\text{Number of full-time workers}},\\ &= \frac{\text{Number of injury and illness cases} \times 200{,}000}{\text{Employee hours worked}},\end{aligned} \tag{1}$$

where 200,000 corresponds to 100 workers working 40 hours per week for 50 weeks per year. We focus on two injury and illness rates: the total case rate (TCR), which

[6] The distinction between injuries and illnesses was eliminated in 2002.

[7] Additional background information on non-fatal workplace injuries and illnesses in the U.S. can be found in *Chapter 9: Occupational Safety and Health Statistics, BLS Handbook of Methods*.

[8] According to *Chapter 9: Occupational Safety and Health Statistics, BLS Handbook of Methods* (p.14), industry estimates may not be published if: (i) publication might disclose confidential information, (ii) the relative standard error of the estimate for days away from work, job transfer, or restriction cases for the industry exceeds a specified limit, or (iii) the benchmark factor for the industry falls outside an acceptable range.

[9] Among the 4-digit industry-year cells, the attrition rate is approximately 20% because only around 80% have available SOII data.

covers all recordable cases, and the days away, restricted, and transfer case rate (DART). DART cases are defined as "those which involve days away from work (beyond the day of injury or onset of illness), or days of job transfer or restricted work activity, or both."[10] As DART covers more serious injury and illness cases that are less prone to misreporting, its use alleviates concerns about imperfect reporting (Ruser, 2008).

Our analysis does not include fatal injuries, as these are very rare. The BLS records include only 4,500-6,600 cases of fatal work injury per year between 1992 and 2014. Between 2006 and 2014, the rate of fatal work injuries was 0.0033-0.0042 per 100 full-time workers.[11] In contrast, the average non-fatal injury and illness rate was approximately 4-12 per 100 full-time workers between 1991 and 2012.

2.2 Import competition

To measure import competition in the U.S., denoted by $impr_{jt-1}$, we follow Acemoglu et al. (2016) and define:

$$impr_{jt} = \frac{\text{Chinese imports to the U.S.}_{jt}}{\text{Industry shipment}_{j,1991} + \text{Industry import}_{j,1991} - \text{Industry export}_{j,1991}}. \tag{2}$$

Their data are obtained from the UN Comtrade Database, which contains bilateral import data on 6-digit Harmonized Commodity Description and Coding System (HS) products. The import values are converted to USD rates in the year 2007 using the personal consumption expenditure deflator.

As explained in Section 3, we address potential endogeneity issues in the estimation by instrumenting the Chinese import penetration ratio in the U.S. with the corresponding Chinese import penetration ratios in eight other countries (Germany, Switzerland, Spain, Denmark, Finland, Japan, Australia, and New Zealand). This instrument is defined as

$$impr^{IV}_{jt} = \frac{\text{Chinese imports to other high income countries}_{jt}}{\text{Industry shipment}_{j,1991} + \text{Industry import}_{j,1991} - \text{Industry export}_{j,1991}}. \tag{3}$$

2.3 Other variables

In the empirical analysis, we also control for a number of industry-level characteristics, including employment, the capital–labor ratio, the share of production workers,

[10] For example, consider two employees who are injured at work. Employee A can continue to work at the same position on the day of the injury. Employee B must be away from work for 5 days, and when they return to work, they are unable to perform normal duties for another 3 days. TCR records both cases, whereas DART only records employee B's case as one case involving 8 days of abnormal work.

[11] These numbers are obtained from presentations by the BLS, available at http://www.bls.gov/iif/oshwc/cfoi/cfch0013.pdf.

safety compliance (proxied by the number of OSHA inspections), and unionization.[12]

To construct employment, the capital–labor ratio, and the share of production workers, we use data from the NBER-CES Manufacturing Industry Database.[13] The number of OSHA inspections is based on data from OSHA Enforcement.[14] For unionization, we use CPS data to measure the share of employees with union coverage or membership in each industry-year.[15]

2.4 Summary statistics

Table 1 reports the summary statistics of the variables. In the sample, each observation corresponds to a 3-digit SIC industry by year. During the 1992–2011 there are 2280 observations with available data on injury and illness rates and import competition. The corresponding sample size with available values for OSHA inspection and unionization is approximately 10% smaller because the underlying raw data are different.[16]

Table 1: Summary statistics

	Observations	Mean	S.D.
Injury and illness rates per 100 full-time workers, R_{jt}			
- Total case rate (TCR)	2280	7.578	4.335
- Days away, restricted, and transfer case rate (DART)	2280	3.708	1.948
Lagged import competition			
- from China to the U.S., $impr_{jt-1}$	2280	0.076	0.151
- from China to other high-income countries, $impr^{IV}_{jt-1}$	2280	0.067	0.128
Employment (1,000 workers)	2280	33.489	35.679
Capital-labor ratio	2280	100.322	117.638
Share of production workers	2280	0.722	0.107
OSHA inspection	2261	251.900	393.184
Unionization	2080	0.041	0.044

Note: Each observation is a 3-digit SIC industry by year. The sample period is 1992-2011.

Per 100 full-time workers, a manufacturing industry witnesses around 7.6 cases of workplace injuries and illnesses (i.e., TCR) each year; of these, approximately 3.7 cases are relatively serious (i.e., DART). The average Chinese import penetration ratio for a typical industry in the U.S. is around 7.6%, and that of the other 8 high-income countries investigated is around 6.7%. The relatively large standard deviations of these variables confirm that there is sufficient variation to draw inferences.

[12]See Section 3 for a discussion of why these variables are used.

[13]See https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.

[14]The OSHA Enforcement data contain establishment-level data about inspections and violation cases in workplaces in different industries. These data are available at http://enforcedata.dol.gov/views/data_summary.php.

[15]We construct this variable as the share of workers in the working-age population who indicate that they are covered by a union or have union membership. Note that in the CPS data, the industry classification is denoted by ind1990. We use the concordance files provided by David Dorn (https://ddorn.net/data.htm) to match ind1990 to 3-digit SIC data.

[16]To construct unionization, we need to convert the industry classification of CPS (ind1990) to a 3-digit SIC. Imperfect matching reduces the sample size.

3. Econometric specifications

3.1 Level and long-difference specifications

Following Lu and Ng (2013), we run the following estimation to identify the link between import competition and workplace injury and illness rates across industries and over time:

$$R_{jt} = \alpha_j + \beta \log(impr_{jt-1}) + \gamma X_{jt-2} + \theta_t + \varepsilon_{jt}, \tag{4}$$

where R_{jt} measures the annual workplace injury and illness rate of industry j in year t; $\log(impr_{jt-1})$ is the log Chinese import penetration ratio (lagged by a year); X_{jt-2} is a vector of covariates (lagged by two years); α_j and θ_t the industry and year fixed-effects, respectively; and ε_{jt} is the error term. If correctly estimated, a negative value of β implies that industries exposed to higher import competition experience lower rates of workplace injury and illness.

In the vector X_{jt-2}, we include employment, the capital–labor ratio, the share of production workers, OSHA inspections, and unionization, which are also used in recent studies on workplace safety and health.[17] Employment is included to control for the industry size. At the firm level, larger firms tend to have lower injury rates (e.g. Hummels, Munch, and Xiang 2016); however, it is unclear whether industries with more workers also have higher injury rates. The capital-labor ratio and share of production workers are proxies for capital input and the use of high versus low-skilled workers in the industry, respectively. Industries using more capital input or low-skilled workers are expected to have higher injury rates (see, e.g., Hummels, Munch, and Xiang 2016 for worker-level evidence).According to the occupational health literature, OSHA inspections tend to decrease workplace injuries (e.g., Li and Singleton 2019). Other studies in this area document that unionized workers are more likely to be injured than non-unionized workers (e.g., Donado 2015).

When estimating model (4), the use of OLS leads to biased estimates. In addition to sector-wide safety policies, enterprises are subject to industry-specific safety policies and regulations. Safety policies encompass many different dimensions and affect industries differently. For instance, safety guidelines that apply to using chemicals have a greater effect on toy industries than on apparel industries. Although we include proxies of safety regulations and unionization as baseline controls, we are not aware of any consistent measure that encompasses all of the different safety dimensions across industries and over time. The share of unionized workers is at

[17] See, e.g. Hummels, Munch, and Xiang (2016), Donado (2015), Li and Singleton (2019), and Li, Rohlin, and Singleton (2022).

best an imperfect measure of the *strength* of unionization and attention to workplace safety. We note that imports are likely also affected by industrial safety policies that we fail to control, thus biasing our β estimates.

We address endogeneity issues by instrumenting the Chinese import penetration ratio in the U.S. with the corresponding ratios in eight other countries (Germany, Switzerland, Spain, Denmark, Finland, Japan, Australia, and New Zealand), denoted as $impr_{jt}^{IV}$ and defined in (3). Autor, Dorn, and Hanson (2013) and Acemoglu et al. (2016) also use this instrument. Its validity hinges on two identification assumptions. First, industry-specific changes (e.g. changes in safety policies, union strength, or worker advocacy groups) in the U.S. do not synchronize with corresponding changes in the other countries. Second, Chinese manufacturing industries do not exhibit strong increasing returns to scale; if the opposite is true, increasing exports to the U.S. would increase an industry's efficiency in terms of exporting to the other eight countries.

Model (4) uses the full time series of injury and imports data. One potential issue with this approach is that using the full time series data could invalidate the instrument when demand shocks are correlated across different countries. To address this issue, we use an alternative long-difference specification similar to the ones used by Autor, Dorn, and Hanson (2013) and Acemoglu et al. (2016):

$$\Delta R_j = \beta\, \Delta \log(impr_j) + \gamma X_{j,1991} + \lambda \Delta R_j^{Pre} + \Delta\varepsilon_j, \tag{5}$$

where j is an industry, ΔR_j and $\Delta \log(impr_j)$ are the annualized changes in R_j and $\log(impr_j)$ between 1991 and 2011, respectively.[18] $X_{j,1991}$ is a vector of control variables measured in 1991 (the initial year), ΔR_j^{Pre} measures the pre-sample period (annualized) change in injury rate for each industry (e.g., over 1981–1991) and is used to control for the pre-existing trends of workplace safety (similar to Acemoglu et al. 2016). As in the level specification in (4), we instrument $\Delta \log(impr_j)$ by $\Delta \log(impr_j)^{IV}$.

Note that the inclusion of the initial control variables in (5) effectively allows for differential trends across industries with different initial values in these variables. The coefficients of these variables are not directly comparable to the coefficients of their time-varying counterparts in the level specification in (4). To emphasize these differences, we include time subscripts to these variables in the regression results presented in Tables 2 and 3 below.[19]

[18]To be precise, $\Delta y_j = \frac{y_{j,2011} - y_{j,1991}}{2011-1991+1}$ for $y_j = \{R_j, \log(impr_j)\}$.

[19]For instance, in the level regressions, we write "log Employment$_{j,t-2}$" whereas in the long-difference regressions, we write "log Employment$_{j,1991}$."

3.2 Other estimation concerns

Before proceeding, we discuss a few other concerns regarding estimation. First, we cannot completely rule out the possibility that the Chinese import penetration ratios of the other eight high-income countries correlate with our error term, which would violate the exclusion restriction. For instance, the Internet might facilitate the coordination of political actions taken by activists around the world. If enough groups of worker-activists from these countries coordinated with their U.S. counterparts to compel the World Health Organization (WHO) or other international health authorities to implement certain industry-specific safety changes, our IV would fail the exclusion restriction. In addition, if enough industries were dominated by a few multinational enterprises with operations both in the U.S. and the other countries, company-wide safety instructions could be synchronized across all nine countries, and our IV might still fail the exclusion restriction.

Second, it remains unclear whether firms facing tougher foreign competition become less likely to report workplace accidents. If enough firms do so, under-reporting may explain the association between import competition and lower workplace injury and illness rates. One possible channel for this association involves the association between lax workplace safety enforcement and more severe under-reporting in some regions (Morantz 2007 and Ruser and Smith 1988). If enforcers become more lenient with firms facing tougher competition, then import competition would correlate with the strictness of workplace safety enforcement, an omitted variable that we can only imperfectly control with our safety regulation proxy (i.e., OSHA inspection). We are unsure whether enforcers indeed treat firms facing tough competition more leniently. One way to gauge this potential bias is to determine whether under-reporting is generally correlated with improved workplace safety. Conway and Svenson (1998) find that audits done in 1987 and 1996 largely indicate the same rate of under- reporting, suggesting that safety improvements during that decade cannot be due to increased under-reporting. Our industry-level analysis also partially alleviates concerns about enforcement variation across regions. Finally, the results pertaining to DART, which covers more serious cases, are less likely to be due to potential under-reporting, at least to the extent that more serious accidents are less likely to be under-reported.

Third, in the estimations of models (4) and (5), we weigh the observations by initial industry size (e.g., employment in 1991). We thus provide an average competition effect that accounts for the sizes of different industries. Weighting also enables more precise coefficient estimates by correcting for heteroskedasticity (Solon, Haider, and Wooldridge 2015). In Section 4.3, we re-estimate these models without sampling weights and obtain similar results.

4. Empirical results

4.1 Baseline results

Table 2 reports the estimation results of model (4) by 2SLS. In these specifications, the observations are weighted by employment in 1991 and the standard errors are clustered at the industry level. Panel A of Table B in Appendix B reports the first-stage results.

Table 2: Baseline results: Level specification

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	TCR			DART		
log ($impr_{jt-1}$)	-1.020^{**}	-1.069^{*}	-1.056^{*}	-0.349^{*}	-0.324	-0.307
	(0.473)	(0.551)	(0.556)	(0.178)	(0.205)	(0.206)
log Employment$_{jt-2}$	0.805	0.865	0.840	0.229	0.264	0.192
	(0.822)	(0.845)	(0.911)	(0.338)	(0.346)	(0.378)
log Capital-labor ratio$_{jt-2}$	3.516^{***}	3.493^{***}	3.535^{***}	1.399^{***}	1.443^{***}	1.479^{***}
	(0.854)	(0.898)	(0.906)	(0.317)	(0.326)	(0.332)
Share of production workers$_{jt-2}$	12.683^{**}	13.528^{**}	13.563^{**}	7.046^{***}	7.558^{***}	7.363^{***}
	(5.728)	(6.270)	(5.981)	(2.576)	(2.841)	(2.641)
Unionization$_{jt-2}$		2.524	2.464		0.367	0.355
		(1.689)	(1.687)		(0.721)	(0.723)
log OSHA inspection$_{jt-2}$			0.076			0.140
			(0.342)			(0.150)
Observations	2280	2080	2061	2280	2080	2061
F-stat for weak id	21.995	19.874	19.594	21.995	19.874	19.594

Note: Sample period is 1992-2011. All regressions include industry and year fixed-effects. All observations are weighted by 1991 employment. Standard errors, clustered at the industry level, are reported in parentheses. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level. The first-stage estimation results are reported in Panel A of Table B in Appendix B.

Columns (1)-(3) use all workplace injuries and illnesses (i.e., TCR) as the outcome variable. Column (1) shows the results when we regress TCR on the log import penetration ratio and a vector of control variables (employment, the capital-labor ratio, and the share of production workers) with industry and year fixed effects. The log import penetration ratio is instrumented by the corresponding log import penetration ratios of the eight other high-income countries. Columns (2) and (3) further controls for unionization and OSHA inspection. The coefficients of log($impr_{jt-1}$) in these specifications are negative and significant. In Columns (4)-(6), we report a similar set of results using DART as the outcome variable. The estimated coefficients of the regressor of interest remain negative but have weaker statistical significance.

We also compare and contrast the coefficient estimates of the control variables with other related studies in the literature. It is important to keep in mind that our analysis is conducted at the *industry* level while other studies may use different units of analysis.[20] Besides, our IV strategy only addresses the potential endogeneity of

[20]Some empirical studies in the economics and occupational health literature are conducted at the establishment or workplace level rather than at the industry level.

our regressor of interest, but not that of the control variables. Thus, we cannot claim that the coefficient estimates of the control variables are unbiased.

First, employment is used to control for industry size. Our results seem to suggest that industry level injury rate has no correlation with employment. While Hummels, Munch, and Xiang (2016) document that workers in larger firms are less likely to be injured, it is unclear whether larger industries also have higher injury rates. Second, we use the capital-labor ratio and share of production workers to proxy for capital input and the use of high-versus low-skilled workers in the industry. Hummels, Munch, and Xiang (2016) find that the likelihood of injury at the worker level is positively associated with the capital-labor ratio and the share of high-skilled workers in the firm. In our case, we also find consistent evidence at the industry level: we find a positive association between the capital-labor ratio and share of production workers (which should be negatively related to the share of high skilled workers). Third, regarding the relationship between workplace injury and unionization, the evidence in the literature seems mixed. Donado (2015) finds that unionized workers are more likely to be injured than non-unionized workers. This union-nonunion "injury gap" is found to be smaller after taking into account individual fixed effects. On the other hand, Li, Rohlin, and Singleton (2022) find that unionization has no detectable effect on injury rates at the mean. In our analysis, we also find an insignificant association. Finally, regarding the relationship between OSHA inspection and workplace injury, recent studies find that (randomized) inspection tend to reduce workplace injury. For instance, Li and Singleton (2019) find that OSHA's "Site-Specific Targeting" (SST) inspections reduced workplace injury at the inspected establishments. Note that SST program was implemented in 1999; establishments may be selected for inspection randomly (if they did not file the workplace injury recordkeeping forms to OSHA) or when they have elevated or upward trending injury rates in the preceeding years.[21] In our analysis, we do not find any significant association between OSHA inspection and injury rate; one possibility is that our industry-level inspection measure does not differentiate random or targeted inspection.

The coefficient estimates for the control variables in Columns (1)-(3) are similar in terms of values and statistical significance; the same applies the coefficient estimates for the control variables in Columns (4)-(6). Besides, those using TCR as the outcome variable (Columns (1)-(3)) are larger than those using DART as the outcome variable (Columns (4)-(6)).

Next, we consider the regression results using the long-difference specification in model (5), reported in Table 3. In these specifications, observations are weighted

[21] See p.4 of https://www.osha.gov/sites/default/files/enforcement/directives/CPL_02-01-062.pdf.

by employment in 1991, and robust standard errors are computed. Panel B of Table B in Appendix B reports the first-stage results. The vectors of the control variables in different columns are similar to those in Table 2, and these variables are measured by their 1991 values rather than their annualized changes. In addition, we control for pre-existing trends of workplace safety. In all of these different specifications, we obtain negative and significant coefficients for $\Delta \log(impr_j)$.[22]

Table 3: Baseline results: Long-difference specification

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:		Δ TCR			Δ DART	
Δ log ($impr_j$)	-1.814^{***}	-1.819^{***}	-1.664^{***}	-0.952^{***}	-0.951^{***}	-0.921^{***}
	(0.340)	(0.415)	(0.420)	(0.166)	(0.199)	(0.206)
log Employment$_{j,1991}$	0.029	0.028	0.055^{**}	0.012	0.012	0.018
	(0.023)	(0.024)	(0.027)	(0.011)	(0.012)	(0.013)
log Capital-labor ratio$_{j,1991}$	0.042^{**}	0.057^{**}	0.058^{**}	0.026^{**}	0.034^{***}	0.034^{***}
	(0.021)	(0.024)	(0.023)	(0.010)	(0.011)	(0.011)
Share of production workers$_{j,1991}$	-0.458^{***}	-0.455^{***}	-0.394^{***}	-0.181^{***}	-0.183^{***}	-0.170^{***}
	(0.093)	(0.097)	(0.100)	(0.045)	(0.047)	(0.049)
Unionization$_{j,1991}$		-0.878^{*}	-0.891^{**}		-0.499^{**}	-0.502^{**}
		(0.463)	(0.445)		(0.205)	(0.203)
log OSHA inspection$_{j,1991}$			-0.031^{*}			-0.006
			(0.017)			(0.008)
Δ TCR$_{j,1991-1981}$	1.196^{***}	1.139^{***}	1.148^{***}			
	(0.138)	(0.150)	(0.145)			
Δ DART$_{j,1991-1981}$				1.045^{***}	1.042^{***}	1.056^{***}
				(0.197)	(0.198)	(0.196)
Observations	100	91	91	100	91	91
F-stat for weak id	93.266	66.350	60.075	89.092	64.131	58.571

Note: All observations are weighted by 1991 employment. The control variables are measured in 1991. Robust standard errors are reported in parentheses. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level. The first-stage estimation results are reported in Panel B of Table B in Appendix B.

In unreported analyses, we also estimate the same regressions by OLS. We find that the 2SLS estimates are larger than the corresponding OLS estimates, suggesting the possibility of omitted variable bias in the OLS estimation. As discussed earlier, industry-specific changes in organizations may be an omitted variable. If industries facing weaker foreign competition have stronger unions and worker advocacy groups and also undergo more rapid improvements in workplace safety, then ignoring this factor in the OLS estimation could bias the estimate of interest upwards.

Overall, the two sets of results seem to support the view that import competition is associated with lower rates of injury and illness in U.S. manufacturing industries. The finding is unlikely to be driven entirely by the possibility of under-reporting of workplace injuries and illnesses under increased pressure from foreign competition.

We acknowledge that the finding obtained from the level specification is weaker. Since our level specification and long-difference specification have their own advantages and disadvantages, we cannot say that one specification is strictly

[22]Note that the first-stage F-statistics are stronger in the long-difference specifications than in the corresponding level specifications.

superior than the other. In our context, the long-difference specification could address the potential issue that demand shocks are correlated across different countries which could invalidate the instrument. These results, however, are based on a smaller sample. On the other hand, the level specification makes use of time-varying variations. However, the regression results are weaker once unionization and OSHA inspections are controlled for. One potential issue of the level specification is that import competition can affect unionization. For instance, Ahlquist and Downey (2021) and Charles, Johnson, and Tadjfar (2021) both document that, at the industry level, higher import competition reduces unionization.[23] In this case, the "bad control" problem (Angrist and Pischke, 2009) may arise, biasing the coefficient estimate of the import competition measure. Therefore, after taking into account all the empirical evidence (including the economic significance reported in the next section), readers are reminded to be cautious in the interpretations of our findings.

Our results complement the recent literature on the impact of import competition on health outcomes. In particular, McManus and Schaur (2016) find that at the establishment level, import competition is associated positively with workplace injury rates in small establishments. Our industry-level results suggest that at an aggregate level, import competition is associated with a lower rate of workplace injury and illness when compositional changes are taken into account (these results are presented in Section 5).

4.2 Economic significance

We perform a back-of-the-envelope calculation of the economic significance of our baseline regression results. We first use the level specification results in Table 2. We consider an increase of *impr* from the first quartile (= 0.003) to the third quartile (= 0.071) and we evaluate the effect at the mean (= 0.076). In other words, the change in injury rate is roughly $\widehat{\beta} \times \Delta impr/impr$. The results in Column (3) of Table 2 suggest that the implied change in TCR is about –0.945 ($\approx -1.056 \times \frac{0.071-.003}{0.076}$) and the implied change in DART is about –0.275 ($\approx -0.307 \times \frac{0.071-.003}{0.076}$).[24] These changes are equivalent to about 12.2% and 6.3% of the corresponding means of TCR and DART.

Alternatively, we use the long-difference specification results in Table 3 to estimate the changes in number of injury cases. In the regression sample, the average annualized change in log import penetration ratio (i.e., $\overline{\Delta \log(impr_j)}$) is approximately 0.1626. This "average industry" has an implied annualized change in TCR of approximately –0.2706 ($\approx -1.664 \times 0.1626$, where –1.664 is the coefficient

[23] In other U.S. industries competition has been found to weaken unions (Holmes and Schmitz Jr., 2010), whether the competition is domestic (as in the U.S. long-distance shipping industry in the 19th and 20th centuries) or foreign (as in the U.S. Iron ore and cement manufacturing industries).

[24] The corresponding standard errors (bootstrapped by 1,000 times) are 0.232 and 0.091.

of $\Delta \log(impr_j)$ in Column (3)of Table 3). As the average employment per industry is roughly 33,000 and the full sample includes 134 distinct industries, the implied annual total reduction in injury cases is roughly $12,000$ cases ($\approx \frac{-0.2706}{100} \times 33,000 \times 134$).[25] If we focus on the more serious cases, the implied annualized change in DART is approximately –0.1498 ($\approx -0.921 \times 0.1626$, where -0.921 is the coefficient of $\Delta \log(impr_j)$ in Column (6) of Table 3) and the annual total reduction in more serious injury cases is roughly $6,600$ cases ($\approx \frac{-0.1498}{100} \times 33,000 \times 134$).

In both sets of calculations, we can see that the economic significance for DART has a smaller magnitude, which is expected because by construction, DART only focuses on more serious injury and illness cases.

Finally, based on the long difference specification results, we estimate the injury costs that the increased import competition could have saved. Using the estimate from Leigh (2011), the per-case cost of an injury (as of 2007) is roughly \$23,000. Assuming that this per-case cost is constant across industries over the sample period, an increase in import competition over the sample period would have saved the manufacturing sector roughly \$276 million ($\approx 12,000 \times \$23,000$). To better comprehend the magnitude of this impact, we compare the change in TCR predicted by import competition according to the model including the actual change observed in the data. For the sample presented in Column (3) of Table 3, the average annualized change in TCR (i.e., $\overline{\Delta \text{TCR}_j}$) is approximately –0.4049. Thus, the model can explain approximately 66.83% ($\approx \frac{-0.2706}{-0.4049} \times 100\%$) of the variation.

4.3 Robustness checks

In this section, we report the results from several robustness checks. The first check is a placebo test, in which we examine whether current import competition can explain past workplace safety. The results are reported in Panels A and B of Table 4. In Panel A, the dependent variable for industry j in year t is $R_{j,t-10}$, and we re-estimate the baseline linear model (4).[26] In Panel B, the dependent variable for industry j is $\Delta R_{1991-1981}$, and we re-estimate the baseline long difference model (5).[27] The results in both panels suggest that current import competition does *not* explain past injury and illness rates.

In a way, the long-difference specification in model (5) takes into account industry-specific time trends, whereas the level specification in model (4) does not. In the second robustness check, we consider a specification similar to model (4) by

[25] Recall from (1) that the injury and illness rate is per 100 workers.

[26] The control variables in various columns are the same as the corresponding columns in Table 2.

[27] The control variables in various columns are the same as the corresponding columns in Table 3 except the pre-existing trends.

Table 4: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Placebo test - level specification					
Dependent variable:	TCR_{t-10}			$DART_{t-10}$		
log ($impr_{jt-1}$)	−0.179	−0.054	−0.022	−0.169	−0.114	−0.111
	(0.437)	(0.485)	(0.514)	(0.187)	(0.212)	(0.224)
Observations	2089	1903	1897	2089	1903	1897
F-stat for weak id	20.613	18.501	18.302	20.613	18.501	18.302
	Panel B: Placebo test - long-difference specification					
Dependent variable:	Δ $TCR_{1991-1981}$			Δ $DART_{1991-1981}$		
$\Delta \log(impr_j)$	−0.216	−0.114	−0.152	0.076	0.082	0.059
	(0.329)	(0.344)	(0.335)	(0.099)	(0.108)	(0.105)
Observations	100	91	91	100	91	91
F-stat for weak id	39.096	27.892	26.187	39.096	27.892	26.187
	Panel C: Including time trends in 1-digit sectors					
Dependent variable:	TCR			DART		
log ($impr_{jt-1}$)	−0.634**	−0.684*	−0.686*	−0.216	−0.209	−0.198
	(0.286)	(0.362)	(0.371)	(0.135)	(0.170)	(0.176)
Observations	2280	2080	2061	2280	2080	2061
F-stat for weak id	24.769	26.649	25.909	24.769	26.649	25.909
	Panel D: Unweighted regressions - level specification					
Dependent variable:	TCR			DART		
log ($impr_{jt-1}$)	−0.715**	−0.716*	−0.715*	−0.252	−0.217	−0.208
	(0.360)	(0.387)	(0.391)	(0.157)	(0.166)	(0.166)
Observations	2280	2080	2061	2280	2080	2061
F-stat for weak id	71.412	68.881	68.415	71.412	68.881	68.415
	Panel E: Unweighted regressions - long-difference specification					
Dependent variable:	Δ TCR			Δ DART		
$\Delta \log(impr_j)$	−1.745***	−1.721***	−1.573***	−0.843***	−0.872***	−0.838***
	(0.327)	(0.376)	(0.373)	(0.201)	(0.231)	(0.232)
Observations	100	91	91	100	91	91
F-stat for weak id	58.385	48.511	46.704	55.157	45.417	43.943

Note:

- For Panels A, C, and D: All regressions include industry and year fixed-effects. The control variables in various columns are the same as the corresponding columns in Table 2. Standard errors, clustered at the industry level, are reported in parentheses.
- For Panels B and E: The control variables in various columns are the same as the corresponding columns in Table 3, except that in Panel B, the pre-existing trends are not included. Robust standard errors are reported in parentheses.
- For all panels: All observations are weighted by 1991 employment. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level.

adding flexible sector-specific time trends.[28] As shown in Panel C, the coefficients of $\log(impr_{jt-1})$ are negative and remain significant for the TCR outcome.

In Panels D and E, we re-estimate the baseline level and long difference specifications [in models (4) and (5)] without weighting the observations by the employment in 1991. In these regressions, the estimated coefficients are less precise and have smaller magnitudes. In particular, the coefficients of $\log(impr_{jt-1})$ in

[28] More precisely, we consider 10 one-digit sectors (as in Acemoglu et al. 2016) and add a quadratic time trend for each sector. Using a linear time trend gives similar but less significant results and weaker first-stage *F*-statistics.

Columns (4)-(6) of Panel D become insignificant. Otherwise, we obtain negative and significant coefficients for the regressors of interest in other specifications.[29]

In an unreported analysis, we use a difference-in-differences specification that exploits the granting of Permanent Normal Trade Relations (PNTR) to China when it entered the World Trade Organization (WTO) in 2001, as in Pierce and Schott (2016). We use a similar approach to examine the impact of this policy change on injury rates but we do *not* find any impact. A further examination of the data reveals that the "parallel trends" assumption does not seem to hold in our context.[30]

5. Compositional changes

Although many studies show that foreign competition displaces U.S. domestic jobs, we examine whether different types of jobs are displaced at different rates. Foreign competition might increase safety in manufacturing workplaces by displacing dangerous jobs at a more rapid rate than safe jobs. We examine this potential channel from multiple angles in Sections 5.1 and 5.2.[31] In Section 5.3, we briefly discuss how our results complement the existing literature.

5.1 The composition of jobs in the manufacturing sector

Understanding the channels through which foreign competition affects workplace safety in the manufacturing sector requires us to determine the link between the composition of jobs in this sector and workplace safety and how this link changes over time.

5.1.1 How is the composition of jobs linked to workplace safety?

First, we correlate the share of production workers with the rate of workplace injuries and illnesses at the industry level. Figure 1(a) shows that industries with a higher share of production workers tend to have a higher rate of workplace injuries and

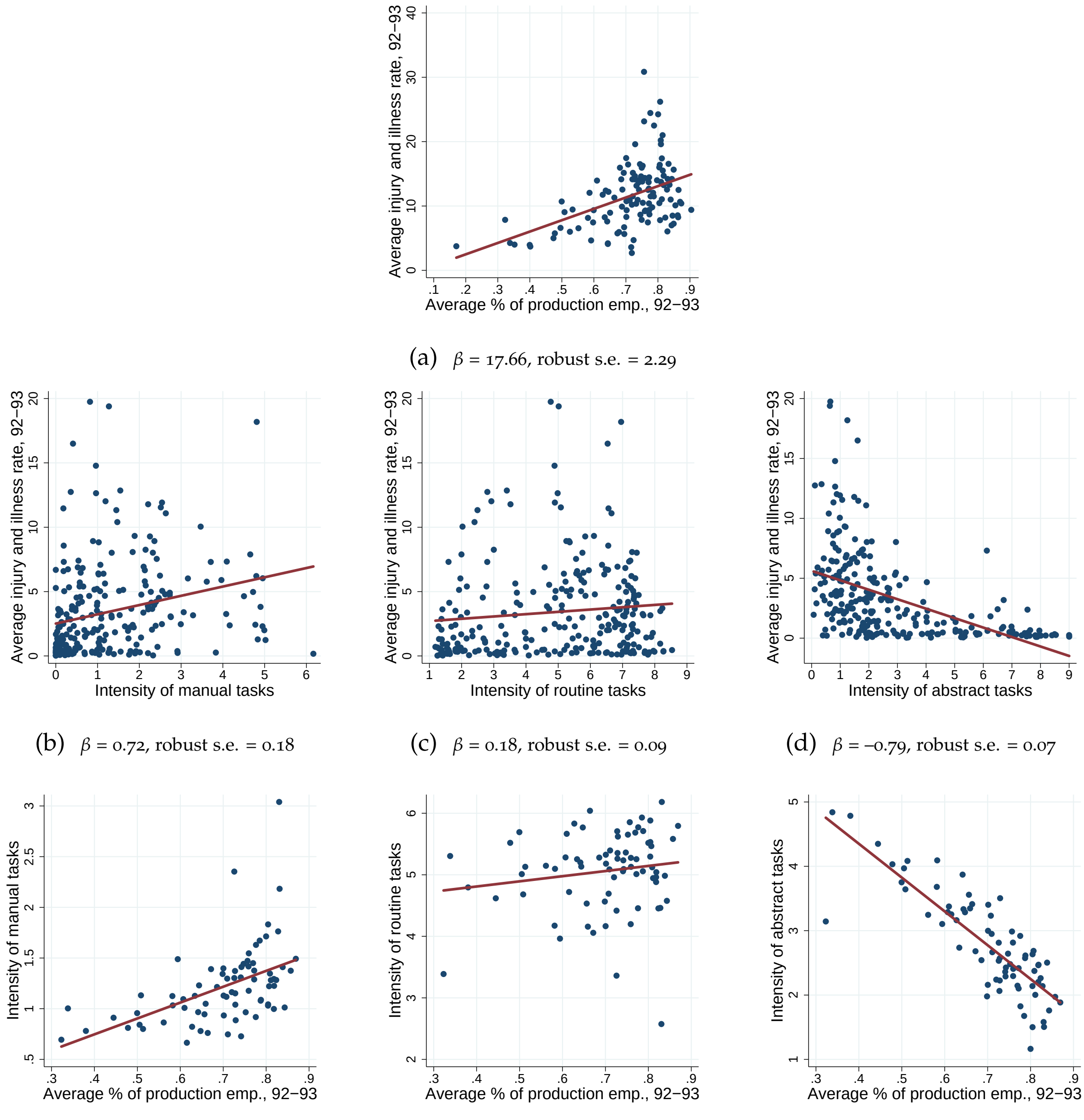
[29]Comparing the coefficients of $\Delta \log(impr_j)$ in Table 3, Column (3) (i.e., –1.664) and Panel E, Column (3) (i.e., –1.573), we see that the weighted and unweighted regression results are similar, suggesting that the economic significance based on the unweighted regression results should also be similar to the results reported in Section 4.2.

[30]Specifically, Pierce and Schott (2016) define the "NTR gap" as the difference between the non-NTR and the NTR tariff rate and examine changes in U.S. manufacturing employment after China's WTO accession. In our case, we regress the injury outcomes on the interaction between the "NTR gap" and the year dummies and find that some of the pre-2001 are statistically significant.

[31]In other unreported analyses, we have examined whether import competition makes jobs safer and whether import competition affects workplace safety through its potential impact on firms' occupational and safety violation and on OSHA's safety inspection. In both cases, we do not find supportive evidence.

illnesses.[32] The jobs performed by production workers appear to be more dangerous than those performed by non-production workers.

Figure 1: Relationship between injury and illness rate, task intensity, and production employment



(a) β = 17.66, robust s.e. = 2.29

(b) β = 0.72, robust s.e. = 0.18

(c) β = 0.18, robust s.e. = 0.09

(d) β = −0.79, robust s.e. = 0.07

(e) β = 1.57, robust s.e. = 0.29

(f) β = 0.84, robust s.e. = 0.71

(g) β = −5.25, robust s.e. = 0.62

Second, we look closely at job tasks. In Figures 1(b) to (d), we sort occupations along the horizontal axis by the intensities of manual, routine, and abstract tasks and examine the relationships of these variables with the rates of occupational injury

[32] In Figure 1(a), each observation is a 3-digit SIC industry. To calculate the average share of production employment in an industry over 1992-1993, we use data from the NBER-CES Manufacturing Industry Database. We compute the average industry-level injury and illness rates over this period using data from SOII-AS.

and illness. In these figures, each observation represents an occupation. These task intensity measures are constructed by Autor and Dorn (2013) and derived from the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) 1977.[33] To measure occupational injury and illness rates, we use data from the SOII–Case and Demographics (SOII-C&D) and the March Supplement of the CPS.[34] These figures show that occupations involving relatively more manual tasks, more routine tasks, or fewer abstract tasks tend to be more dangerous, as shown by higher injury and illness rates.

Third, Figures 1(e) to (f) show that at the industry level, the share of production workers is positively correlated with the intensity of manual tasks but negatively correlated with the intensity of abstract tasks.[35]

Note that one might examine the relationship of the intensity of manual tasks relative to abstract tasks (i.e., the manual task measure minus the abstract task measure, as in Autor and Dorn 2013) with the injury and illness rate, and of the intensity of manual tasks relative to abstract tasks with production employment. In an unreported analysis, we find that the relative task intensity is positively correlated with both the rate of workplace injury and illness rate and the share of production employment. However, it is important to consider the intensities of different tasks separately to better distinguish the impacts of import competition and technology on workplace safety.[36]

Finally, we gauge the job compositions of different occupations by the corresponding actual injury rates. Table C in Appendix C shows the most dangerous and safest jobs in the manufacturing sector. Consistent with Figure 1, the most

[33]We also follow Keller and Utar (2019) to construct measures of manual and cognitive task intensities derived from the Department of Labor's Occupational Information Network database (O*NET) and obtain similar results.

[34]SOII-C&D records the number of injury and illness cases by occupation for all industries (up to 2010), and CPS provides data on occupational employment. The injury and illness rate (per 100 workers) for occupation o in year t is computed as R_{ot} = Number of injury and illness cases$_{ot}$/Employment$_{ot}$ $\times$ 100.

[35]Note that the correlation between the share of production workers and the intensity of routine tasks is positive yet insignificant. To create these figures, we calculate the task intensity for an industry as the sum of the corresponding occupational task intensity weighted by the employment shares of different industry occupations (estimated using CPS data). Specifically, we first use CPS data and focus on workers aged between 16 and 65 years. For each worker, we observe the occupation code (occ1990) and industry code (ind1990). As the task intensity measures used by Autor and Dorn (2013) are at the occupation level (occ1990dd, which is similar to occ1990), we can assign task intensity scores to each worker and compute the average task intensity scores during 1992-1993 for different ind1990 industries. Then, we compute industry-level production employment using data from the NBER-CES Manufacturing Industry Database, which uses the 4-digit SIC industry classification. Using the crosswalk provided by David Dorn (https://ddorn.net/data.htm), we then compute the average share of production workers during 1992-1993 at the ind1990 industry-level. Finally, we combine the two to create the scatter plots.

[36]For instance, Autor (2010) finds that technology affects occupations in terms of their routineness, whereas Keller and Utar (2019) show that import competition affects occupations that are manual task-intensive, regardless of the level of routine/non-routine task intensity.

dangerous occupations are exclusively held by production workers, whereas the safest occupations are exclusively held by non-production workers.

5.1.2 How does the composition of jobs change over time?

Table 5 traces changes in the employment shares of the different types of jobs in the manufacturing sector. We sort occupations into quintiles by their average injury and illness rates during 1992-1993 in Panel A and by manual, routine, and abstract task intensities in Panels B, C, and D, respectively. Each number in Columns (1)-(5) is the average injury and illness rate of the occupations in the corresponding quintile bin. Each number in Columns (6)-(10) is the share of manufacturing workers who perform the occupations in the corresponding quintile bin.

Table 5: Trends in occupational injury and illness rates and employment shares

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Average injury and illness rate					Employment share				
Quintile bins / Year		1992	1996	2001	2006	2010	1992	1996	2001	2006	2011
		Panel A: Occupations sorted by average injury and illness rate, 1992-1993									
Bin 1	(Safe)	0.22	0.17	0.13	0.10	0.09	0.14	0.15	0.16	0.17	0.18
Bin 2		0.56	0.45	0.36	0.28	0.27	0.18	0.18	0.18	0.20	0.22
Bin 3	↓	1.88	1.74	1.30	2.04	0.68	0.19	0.18	0.18	0.16	0.16
Bin 4		3.49	2.74	2.25	1.61	1.36	0.24	0.24	0.23	0.22	0.21
Bin 5	(Dangerous)	7.47	5.60	4.14	4.11	3.17	0.25	0.25	0.25	0.24	0.23
		Panel B: Occupations sorted by intensity of manual tasks									
Bin 1	(Less manual)	0.79	0.59	0.46	0.32	0.31	0.13	0.12	0.12	0.14	0.13
Bin 2		1.05	0.84	0.65	0.63	0.55	0.22	0.23	0.25	0.23	0.25
Bin 3	↓	2.60	2.74	2.11	3.52	0.99	0.30	0.28	0.28	0.28	0.31
Bin 4		4.32	3.05	2.24	2.34	1.81	0.22	0.24	0.23	0.20	0.18
Bin 5	(More manual)	3.74	3.06	2.47	1.64	1.37	0.13	0.12	0.13	0.14	0.13
		Panel C: Occupations sorted by instensity of routine tasks									
Bin 1	(Less routine)	1.02	0.75	0.57	0.40	0.39	0.14	0.15	0.16	0.17	0.17
Bin 2		4.13	3.27	2.49	1.94	1.70	0.14	0.15	0.15	0.15	0.13
Bin 3	↓	2.51	2.00	1.57	1.12	0.91	0.17	0.16	0.16	0.20	0.22
Bin 4		2.61	2.37	1.73	2.92	1.24	0.31	0.30	0.30	0.27	0.24
Bin 5	(More routine)	2.05	1.46	1.19	1.28	0.84	0.24	0.24	0.21	0.21	0.24
		Panel D: Occupations sorted by instensity of abstract tasks									
Bin 1	(Less abstract)	5.41	4.22	3.16	2.50	2.12	0.29	0.27	0.27	0.28	0.27
Bin 2		3.20	2.41	1.81	1.44	1.26	0.18	0.18	0.18	0.17	0.15
Bin 3	↓	1.88	1.47	1.22	0.97	0.80	0.16	0.15	0.13	0.13	0.14
Bin 4		1.39	1.46	1.11	3.17	0.68	0.12	0.12	0.13	0.12	0.14
Bin 5	(More abstract)	0.52	0.39	0.31	0.23	0.23	0.25	0.28	0.29	0.29	0.30

Note: Occupations are sorted into quintile bins by average injury and illness rate, 1992-1993 (Panel A), intensity of manual tasks (Panel B), intensity of routine tasks (Panel C), or intensity of abstract tasks (Panel D). Each number in Columns (1)-(5) is the average injury and illnes rate of occupations in the corresponding bin. Each number in Columns (6)-(10) is the share of workers in occupations in the corresponding bin.

Comparing Columns (1) and (5), we find that the occupations in different bins tend to be safer over time irrespective of whether we sort the occupations according to their average injury and illness rate, manul or abstract task intensities. Columns (6) and (10) show that when we sort the occupations by the average injury and illness rate, the employment shares of occupations in Bins 1 and 2 increase, while those in

Bins 3 to 5 decrease over time. We then sort the occupations by task intensities and observe mixed trends. In terms of manual task intensity, the employment shares of occupations in Bins 1 and 5 stay more or less the same, that in Bin 2 increases while that in Bin 4 decreases. Regarding the employment shares of occupations in terms of routine task intensity, there does not seem to be a clear pattern (e.g. the shares of occupations in Bins 1 and 3 increase while those in Bins 2 and 4 decrease). More interestingly, the employment shares of occupations that are less abstract (Bin 1 and Bin 2) tend to decrease, while those of occupations that are more abstract (Bin 4 and Bin 5) tend to increase.

In summary, over time, the composition of the manufacturing sector seems to shift to a lower fraction of dangerous jobs and a higher fraction of safe jobs. Section 5.2 checks whether such changes in job composition are associated with import competition.

5.2 Evidence that import competition drives compositional changes

5.2.1 Does import competition more strongly affect industries employing a higher share of production workers?

To check whether import competition improves workplace safety by displacing dangerous jobs more rapidly than safer jobs, we check whether such competition affects workplace injury and illness rates more strongly in industries employing a higher share of production workers, which are shown in Section 5.1 to involve more dangerous jobs.

The results in Table 6 show that this is indeed the case. Specifically, we add the interaction of the share of production employment in 1991 (denoted as $\overline{E}_j^P$) with $\log(impr_{jt-1})$ in (4), i.e., we estimate the following regression:

$$R_{jt} = \alpha_j + \beta_1 \log(impr_{jt-1}) + \beta_2 \left[\overline{E}_j^P \times \log(impr_{jt-1})\right] + \gamma X_{jt-2} + \theta_t + \varepsilon_{jt}. \quad (6)$$

The coefficients of the interaction terms are both negative and statistically significant, suggesting that import competition likely displaces dangerous jobs at a faster rate, resulting in safer manufacturing workplaces. One caveat is that the NBER-CES Manufacturing Industry Database does not include auxiliary employment (Bartelsman and Gray, 1996), which has also increased among industries in the manufacturing sector.[37]

[37] In an unreported analysis, we use the results in Table 6 and find similar marginal effects of changing import competition on injury rates; besides, we find that industries with larger share of production workers also have higher injury rates.

Table 6: Baseline results: Interactions with production employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	TCR				DART			
$\log(impr_{jt-1})$	2.520***	2.527***	2.356***	2.366***	1.068***	1.077***	1.047***	1.062***
	(0.773)	(0.773)	(0.812)	(0.812)	(0.308)	(0.309)	(0.329)	(0.334)
$\log(impr_{jt-1})\times$ Share of production workers$_{1991}$	−5.328***	−5.330***	−5.076***	−5.078***	−2.167***	−2.166***	−2.071***	−2.070***
	(1.325)	(1.327)	(1.365)	(1.367)	(0.476)	(0.473)	(0.488)	(0.485)
log Employment$_{jt-2}$	−0.804	−0.853	−0.716	−0.769	−0.387	−0.460	−0.346	−0.429
	(0.896)	(0.926)	(0.934)	(0.970)	(0.362)	(0.387)	(0.375)	(0.407)
log Capital-labor ratio$_{jt-2}$	0.801	0.804	0.971	0.975	0.293	0.310	0.411	0.431
	(1.102)	(1.107)	(1.137)	(1.142)	(0.411)	(0.409)	(0.415)	(0.413)
Share of production workers$_{jt-2}$	8.009	7.859	9.419	9.235	5.303**	5.116**	6.066**	5.809**
	(5.495)	(5.356)	(5.921)	(5.723)	(2.368)	(2.253)	(2.572)	(2.417)
log OSHA inspection$_{jt-2}$		0.075		0.077		0.121		0.134
		(0.287)		(0.307)		(0.130)		(0.138)
Unionization$_{jt-2}$			1.118	1.134			−0.155	−0.136
			(1.820)	(1.802)			(0.721)	(0.708)
Observations	2135	2127	1935	1927	2135	2127	1935	1927
F-stat for weak id	7.136	7.001	5.765	5.631	7.136	7.001	5.765	5.631

Note: Sample period is 1992-2011. All regressions are 2SLS regressions. All regressions include industry and year fixed-effects. All observations are weighted by 1991 employment. Standard errors, clustered at the industry level, are reported in parentheses. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level.

5.2.2 Does import competition shift labor away from dangerous occupations?

Columns (6)-(10) of Panel A of Table 5 show that the manufacturing sector includes fewer dangerous jobs and more safe jobs. Does import competition drive these changes? To answer this question, we estimate the following equation:

$$S_{jt}^{d} = \alpha_j + \beta \log(impr_{jt-1}) + \gamma X_{jt-2} + \theta_t + \varepsilon_{jt}, \tag{7}$$

where S_{jt}^{d} is the share of workers in industry j and year t who work in occupations in quintile bin d:

$$S_{jt}^{d} = \frac{\sum_{o\in d} \text{Employment}_{ojt}}{\text{Employment}_{jt}}. \tag{8}$$

In this regression, the industry classification is ind1990. We weight the observations by the industry's employment in 1991 and control for employment, industry, and year fixed effects.

Table 7 reports the results. Columns (1)-(5) respectively use S_{jt}^{1} to S_{jt}^{5} as the dependent variable. In Panel A, the bins are defined by the average injury and illness rates. In Panels B, C, and D, the bins are respectively defined by the intensity of manual tasks, routine tasks, and abstract tasks. In each panel, a positive (negative) and significant coefficient of $\log(impr_{jt-1})$ suggests that the share of workers in the occupations in the corresponding bin increases (decreases) with import competition.

Table 7: Import competition and employment shares of occupations with different degrees of dangerousness/task inputs

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	S^1_{jt}	S^2_{jt}	S^3_{jt}	S^4_{jt}	S^5_{jt}
	Panel A: Occupations sorted by degrees of dangerousness				
log ($impr_{jt-1}$)	1.058**	−0.197	−0.416	0.744	−1.189*
	(0.508)	(0.647)	(0.528)	(0.766)	(0.642)
	Panel B: Occupations sorted by intensities of manual tasks				
log ($impr_{jt-1}$)	−0.311	0.129	1.089	−1.363**	0.457
	(0.535)	(1.091)	(0.987)	(0.559)	(0.631)
	Panel C: Occupations sorted by intensities of routine tasks				
log ($impr_{jt-1}$)	0.560	0.549	0.834	−1.486	−0.457
	(0.435)	(0.606)	(0.748)	(1.017)	(0.813)
	Panel D: Occupations sorted by intensities of abstract tasks				
log ($impr_{jt-1}$)	1.385	−1.904**	0.297	−0.981	1.202*
	(1.051)	(0.950)	(0.404)	(0.756)	(0.706)

Note: $N = 1031$. Sample period is 1994-2011. S^d_{jt} is the share of workers in industry j and year t who work in the occupations in quintile bin d according to the average injury and illness rates in 1992-1993. All regressions are 2SLS regressions and include log Employment, industry, and year fixed-effects. Standard errors, clustered at the industry level, are reported in parentheses. The F-statistic for weak identification is 12.457. All observations are weighted by the 1991 employment. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level.

Therefore, the results in Panel A suggest that in industries facing tougher import competition, the share of workers in the safest occupations increases, while that in the most dangerous occupations decreases.

The results in Panels B-D reveal interesting shifts in the employment shares of occupations according to task intensity. Specifically, the results in Panel B suggest that import competition decreases the share of workers in occupations in Bin 4 (which are relatively more manual task-intensive than other occupations). The results in Panel C suggest that import competition has no significant impact on the shares of workers in occupations with different intensities of routine tasks. Finally, the results in Panel D suggest that import competition decreases the share of workers in occupations in Bin 2 (which are relatively less abstract task-intensive) but increases the share of workers in occupations in Bin 5 (which are the most abstract task-intensive).[38]

5.3 Discussion

Our results complement the findings of Lu and Ng (2013), specifically that industries facing more intense import competition implement more non-routine skill sets, including cognitive and manual skills. Jobs involving cognitive skills are likely to

[38] We can draw similar conclusions if we sort occupations by their manual task intensity relative to abstract task intensity. However, as we discussed in Section 5.1.1, it is important to consider the different task intensities separately. Therefore, we do not report the results based on relative task intensity for brevity.

be safer than jobs involving manual skills. On the other hand, jobs involving non-routine manual tasks are likely to be more dangerous than jobs involving routine manual tasks. Our paper sheds light on the empirical problem regarding the unclear overall impact of import competition on workplace safety. Our findings from multiple angles are consistent with the view that import competition displaces dangerous jobs in the manufacturing sector at a faster rate than safe jobs. The corresponding shifts in employment shares are correlated significantly with the intensity of import competition at the industry level. Such shifts in employment share are observed across occupations, ranging from those with higher to those with lower pre-sample injury and illness rates, and from occupations with relatively more manual tasks to those with relatively more abstract tasks. Consistently, import competition affects workplace injury and illness rates more strongly in industries employing a higher share of production workers.

6. Concluding remarks

In this paper, we examine whether the improvement of the American manufacturing workplace safety can be partly explained by import competition. Aggregate trends show that manufacturing sector workplaces have become safer. Using workplace injury and illness data from the SOII, we find significantly lower workplace injury and illness rates in manufacturing industries facing more intense import competition. We also find that import competition is associated with a lower share of dangerous jobs and a higher share of safe jobs. These associations suggest that import competition displaces dangerous jobs at a faster rate than safe jobs.

To place our results in the broader context, we need to go beyond our confined discussion in the introduction of the literature focusing only on how import competition affects the U.S. labor market outcomes and workplace safety. The broader context asks: how trade, or openness in general, affects health outcomes.

Under this broad context, our paper's focus is necessarily narrow. Our results shed no light on other health outcomes, such as stress, for workers who keep their jobs. We also shed no light on the health outcomes of those who fail to keep their jobs and must be either unemployed or switch to another industry or geographic regions. As mentioned in the introduction, Adda and Fawaz (2020) and Pierce and Schott (2020) find that those living in the U.S. regions more exposed to import competition in general have worse health as measured by a variety of different measures, which suggest that beyond workplace safety, at least some other health dimensions get worsened possibly due to job displacement. Lang, McManus, and Schaur (2019) find that even for employed workers, they are more mentally stressful if they live and work at those U.S. regions more exposed to import competition. This result suggests that even those remain employed can experience negative health impact. Thus, a message we want to get across: our result that the manufacturing workplace safety improvement can partly be explained by import competition does not necessarily imply import competition improves workers' overall health.

Looking beyond the U.S., similar negative effect is documented in the U.K. where workers' mental health significantly worsens when exposed to import competition. Colantone, Crinò, and Ogliari (2019) provide evidence to suggest that trade-induced job displacement is one significant channel. Thus, at least in the U.K., we have reasons to suspect that job displacement, or at least the increased possibility of which, affect workers' health. It is well-documented that import competition significantly displaces jobs in the developed countries such as the U.S. (Acemoglu et al., 2016; Autor and Dorn, 2013; Pierce and Schott, 2016), Denmark (Utar, 2014, 2018), the U.K. (Colantone, Crinò, and Ogliari, 2019), and Germany (Dauth, Findeisen, and Suedekum, 2014), and also in the developing countries such as Mexico (Guerrico, 2021; Utar and Ruiz, 2013). Bloom et al. (2019), however, find that some of the U.S. jobs displaced in the manufacturing sector due to import competition are offset by job gains in the service sector; they also find that jobs appear to reallocate from inland to coastal areas. Consistently, Felbermayr, Prat, and Schmerer (2011) find among 20 OECD countries that trade liberalization decreases, rather than increases, structural unemployment in the long run. This raises an important policy question for future research: when and where do we expect significant frictions to prevent other businesses from springing up to hire those workers who are displaced due to import competition?

Looking at trade and openness from exports instead of imports, Li and Liang (2020) find that the American workerplace safety improves due to an increased in export demand. Similar effect has been documented for workers in China too (Feng, Xie, and Zhang, 2021). Finally, workers' health can be worsened due to firm sales increases as documented by Hummels, Munch, and Xiang (2016) among the Danish workers, as well as by Fan, Lin, and Lin (2020) among the Chinese workers. These interesting results suggest that increased labor demand can increase workplace stress, and possibly their workplace injury and illness rates. These results hint to the possibility that regardless of whether trade affects labor demand negatively or positively, workplace safety and health will be affected.

The overall take of this broad literature is that trade can affect health along multiple dimensions in a variety of different ways through many different channels. Our result offers one particular dimension of how import competition affect industry-level workplace safety and whether the effects are due to non-uniform displacement of safe and dangerous jobs. Our results cannot be generalized to imply that trade improves overall health.

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Appendix

A. A decomposition of the aggregate trends

We decompose the trends of workplace injuries and illnesses to better understand the source of variations. Our decomposition exercise suggests that the variations of workplace safety improvement across industries are especially pronounced. If import competition does affect the safety of the American workplace, it must be able to explain such variations.

Let R_t denote the aggregate injury and illness rate in year t of the economy consisting of the manufacturing sector and other different non-manufacturing sectors (all indexed by k).[39] We may write R_t as a weighted sum of the injury and illness rates in these sectors: $R_t = \sum_k S_{kt} R_{kt}$, where S_{kt} is the employment share of sector k in year t and R_{kt} is the injury and illness rate of sector k in year t. The change in the aggregate injury and illness rate from $t-1$ to t can be decomposed as follows:

$$\Delta R_t = R_t - R_{t-1} = \underbrace{\sum_k \Delta S_{kt} \overline{R}_{kt}}_{\text{“Between”}} + \underbrace{\sum_k \overline{S}_{kt} \Delta R_{kt}}_{\text{“Within”}}, \tag{A.1}$$

where $\overline{x}_t = (x_t + x_{t-1})/2$. The first term (“between”) measures the changes in the aggregate injury and illness rates due to the reallocation of workers across different sectors. The second term (“within”) measures the changes in the injury and illness rates within each sector. Note that, for a given sector k, the sum of the “between” and the “within” components is $\Delta S_{kt} \overline{R}_{kt} + \overline{S}_{kt} \Delta R_{kt} = \Delta(S_{kt} R_{kt})$; this sum measures the contribution of sector s to the change of the aggregate injury and illness rate.

Panel A of Table A shows the results using the aggregate data from various *Annual Reports of Workplace Injuries and Illnesses* published by the Bureau of Labor Statistics (BLS). The unit of different variables is 100 times the annual change of the corresponding variable. The results reveal the following patterns. First, the bottom row shows that, during 1991-1996, workplace safety in the entire economy witnessed rapid improvement. Such an improvement shifted gears and became even more rapid in 1996-2001 and in 2001-2006 but slowed down somewhat in 2006-2011. Second, most of these changes can be attributed to the “within” part. Third, the manufacturing and other major non-manufacturing sectors differ in a way consistent with the overall trends in workplace safety mentioned in the Introduction. The manufacturing sector recorded large reductions in the injury rate in both the “between” component and the “within” component. It contributes substantially to the overall reduction of the aggregate injury and illness rate. In contrast, the other non-manufacturing sectors did not experience the same large reductions, except for the Wholesale and retail trade sector during 2001-2006. In some non-manufacturing sectors, the sums of the “between” component and the “within” component were close to 0 (or even positive, for the Services sector during 1991-1996), suggesting that these sectors did not contribute much to the reduction of aggregate injury and illness rate.

[39] We exclude the public sector in the analysis. We consider the following major non-manufacturing sectors: “Agriculture, forestry, and fishing,” “Mining,” “Construction,” “Manufacturing,” “Transportation and public utilities,” “Wholesale and retail trade,” “Finance, insurance, and real estate,” and “Services.”

Table A: Decomposition of the change in the aggregate injury and illness rate

	1991-1996			1996-2001			2001-2006			2006-2011		
	B	W	$B+W$	B	W	$B+W$	B	W	$B+W$	B	W	$B+W$
	Panel A: Decomposition of the change in the aggregate injury and illness rate											
Manufacturing	−3.09	−9.48	−12.57	−5.61	−10.20	−15.81	−8.77	−6.42	−15.19	−1.99	−4.11	−6.10
Non-manufacturing												
Agriculture, forestry, and fishing	0.38	−0.61	−0.23	0.17	−0.45	−0.28	−0.98	−0.49	−1.47	0.03	−0.07	−0.04
Mining	−0.25	−0.33	−0.58	−0.07	−0.20	−0.27	−0.09	−0.01	−0.10	0.05	−0.16	−0.11
Construction	1.30	−3.43	−2.13	1.60	−2.50	−0.90	0.12	−3.30	−3.18	−1.43	−2.45	−3.88
Transportation and public utilities	−0.50	−0.86	−1.36	0.39	−2.58	−2.19	−3.95	−0.93	−4.88	0.00	−1.22	−1.22
Wholesale and retail trade	−0.86	−4.33	−5.19	−0.83	−6.34	−7.17	−6.67	−7.80	−14.47	−0.10	−3.58	−3.68
Finance, insurance, and real estate	−0.32	0.00	−0.32	0.13	−0.88	−0.75	−0.05	−0.64	−0.69	−0.09	−0.24	−0.33
Services	2.82	−1.12	1.70	2.30	−8.44	−6.14	12.78	−14.22	−1.44	2.02	−4.61	−2.59
Total	−0.52	−20.16	−20.68	−1.92	−31.59	−33.51	−7.61	−33.81	−41.42	−1.51	−16.44	−17.95
	Panel B: Decomposition of the change in the injury and illness rate in the manufacturing sector											
Food and kindred products	0.31	−8.20	−7.89	1.75	−7.78	−6.03	1.03	−7.08	−6.05	2.80	−4.13	−1.33
Tobacco products	−0.06	0.01	−0.05	−0.03	−0.10	−0.13	1.47	0.59	2.06	0.34	−0.36	−0.02
Textile mill products	−0.44	−1.55	−1.99	−0.92	−1.58	−2.50	−0.13	−0.39	−0.52	−0.39	−0.44	−0.83
Apparel and other textile products	−1.31	−1.83	−3.14	−2.14	−1.84	−3.98	−0.98	−0.98	−1.96	−0.17	−0.12	−0.29
Lumber and wood products	1.50	−2.07	−0.57	0.45	−3.10	−2.65	−0.80	−1.76	−2.56	−1.60	−1.38	−2.98
Furniture and fixtures	0.47	−1.96	−1.49	0.32	−0.67	−0.35	2.03	−2.39	−0.36	−1.18	−1.54	−2.72
Paper and allied products	−0.07	−2.45	−2.52	−0.03	−1.40	−1.43	−0.35	−1.19	−1.54	−0.01	−0.60	−0.61
Printing and publishing	−0.06	−1.17	−1.23	−0.45	−2.27	−2.72	−2.98	−0.49	−3.47	−0.27	−1.12	−1.39
Chemicals and allied products	−0.26	−1.82	−2.08	0.22	−0.91	−0.69	0.19	−1.31	−1.12	0.45	−0.65	−0.20
Petroleum and coal products	−0.10	−0.26	−0.36	0.01	−0.26	−0.25	0.01	−0.03	−0.02	0.07	−0.12	−0.05
Rubber and misc. plastics products	1.71	−2.80	−1.09	0.31	−3.87	−3.56	0.29	−2.11	−1.82	−0.24	−2.10	−2.34
Leather and leather products	−0.37	−0.22	−0.59	−0.37	−0.17	−0.54	−0.09	−0.16	−0.25	−0.01	0.01	0.00
Stone, clay, and glass products	0.29	−1.39	−1.10	0.91	−1.45	−0.54	0.44	−2.09	−1.65	−0.56	−1.15	−1.71
Primary metal industries	−0.30	−2.10	−2.40	−0.06	−3.29	−3.35	−1.04	−1.49	−2.53	−0.07	−1.63	−1.70
Fabricated metal products	1.50	−4.56	−3.06	1.32	−5.35	−4.03	4.71	−6.73	−2.02	0.54	−4.43	−3.89
Industrial machinery and equipment	1.14	−2.90	−1.76	−0.11	−6.15	−6.26	−4.11	−1.97	−6.08	0.47	−3.06	−2.59
Electronic and other electric equipment	0.46	−3.17	−2.71	0.35	−3.28	−2.93	−6.27	0.12	−6.15	0.08	−1.24	−1.16
Transportation equipment	−1.90	0.00	−1.90	1.48	−7.35	−5.87	4.71	−10.42	−5.71	−1.28	−6.71	−7.99
Instruments and related products	−0.65	−0.88	−1.53	0.09	−1.03	−0.94	2.71	−2.79	−0.08	0.05	−1.12	−1.07
Miscellaneous manufacturing industries	0.26	−0.74	−0.48	−0.07	−1.30	−1.37	2.66	−1.46	1.20	0.28	−0.86	−0.58
Total	2.12	−40.06	−37.94	3.03	−53.15	−50.12	3.50	−44.13	−40.63	−0.70	−32.75	−33.45

Note: The unit is 100 × the annual change of the relevant variable. B is the "between" component and W is the "within" component.

To understand the changes in the different industries within the manufacturing sector, we use the same method to further decompose the change in injury and illness rate in the manufacturing sector in (A.1), denoted by ΔR_{Mt}:

$$\Delta R_{Mt} = \underbrace{\sum_j \Delta S_{jt} \overline{R}_{jt}}_{\text{"Between"}} + \underbrace{\sum_j \overline{S}_{jt} \Delta R_{jt}}_{\text{"Within"}} . \tag{A.2}$$

where j indexes the individual industries within the manufacturing sector. The first term ("between") measures the changes in injury and illness rates in the manufacturing sector due to the reallocation of workers between different industries within the manufacturing sector. The second term ("within") measures the changes in injury and illness rates for each manufacturing industry. Panel B of Table A shows the results for the 20 2-digit SIC manufacturing industries.[40]

The results suggest that the changes in the manufacturing workplace injury

[40] These industries include: Food and kindred products (20), Tobacco products (21), Textile mill products (22), Apparel and other textile products (23), Lumber and wood products (24), Furniture and fixtures (25), Paper and allied products (26), Printing and publishing (27), Chemicals and allied products (28), Petroleum and coal products (29), Rubber and miscellaneous plastics products (30), Leather and leather products (31), Stone, clay, and glass products (32), Primary metal industries (33), Fabricated metal products (34), Industrial machinery and equipment (35), Electronic and other electric equipment (36), Transportation equipment (37), Instruments and related products (38), and Miscellaneous manufacturing industries (39). Note that the industry classification used in 2006 and 2011 is NAICS. We convert it to SIC to match the earlier data.

and illness rates are mostly due to the "within" component. In each period, there are substantial variations of the "within" term of the different industries. Some industries have rather small reductions (e.g., petroleum and coal products), while others have large reductions (e.g., fabricated metal products). This table suggests that understanding the driver behind the industrial differences of the safety improvement is the key to understanding the safety of the American workplace.

B. First-stage results

Panels A and B of Table B report the first stage regression results for the models in (4) and (5) respectively.

Table B: First-stage results

	(1)	(2)	(3)
	Panel A: Level specification; Dependent variable: $\log(impr_{jt-1})$		
$\log(impr^{IV}_{jt-1})$	0.482***	0.446***	0.442***
	(0.103)	(0.100)	(0.100)
log Employment$_{jt-2}$	0.230	0.170	0.227
	(0.242)	(0.247)	(0.248)
log Capital-labor ratio$_{jt-2}$	−0.586**	−0.565**	−0.567**
	(0.242)	(0.229)	(0.230)
Share of production workers$_{jt-2}$	−1.588	−0.710	−0.509
	(1.346)	(1.433)	(1.438)
Unionization$_{jt-2}$		0.001	−0.008
		(0.541)	(0.550)
log OSHA inspection$_{jt-2}$			−0.073
			(0.077)
Observations	2280	2080	2061
R^2	0.966	0.970	0.971

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel B: Long-difference specification; Dependent variable: $\Delta\log(impr_j)$					
$\Delta\log(impr^{IV}_j)$	0.755***	0.664***	0.644***	0.738***	0.653***	0.635***
	(0.116)	(0.119)	(0.119)	(0.116)	(0.120)	(0.120)
log Employment$_{j,1991}$	−0.014*	−0.012	−0.017*	−0.012	−0.010	−0.015*
	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
log Capital-labor ratio$_{j,1991}$	0.019*	0.024**	0.023**	0.018	0.023**	0.022**
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Share of production workers$_{j,1991}$	0.043	0.026	0.013	0.045	0.030	0.018
	(0.040)	(0.041)	(0.039)	(0.042)	(0.043)	(0.041)
Unionization$_{j,1991}$		0.030	0.032		−0.003	0.000
		(0.130)	(0.126)		(0.120)	(0.117)
log OSHA inspection$_{j,1991}$			0.006			0.006
			(0.007)			(0.007)
Δ TCR$_{j,1991-1981}$	0.052	0.044	0.041			
	(0.043)	(0.046)	(0.040)			
Δ DART$_{j,1991-1981}$				0.145	0.145	0.129
				(0.129)	(0.134)	(0.117)
Observations	100	91	91	100	91	91
R^2	0.926	0.935	0.936	0.926	0.936	0.937

Note:

- For Panel A: All regressions include industry and year fixed-effects. Standard errors, clustered at the industry level, are reported in parentheses.
- For Panel B: Robust standard errors are reported in parentheses.
- For both panels: All observations are weighted by 1991 employment. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level.

C. The most dangerous and safest occupations in the manufacturing sector

Table C lists some of the most dangerous occupations (in Panel A) and the least dangerous occupations (in Panel B) in the manufacturing sector.

Table C: The most dangerous and safest occupations in the manufacturing sector

Occupations	Average injury and illness rate, 1992-1993
Panel A: Most dangerous occupations	
Production helpers	18.34
Washing, cleaning, and pickling machine operators	15.47
Structural metal workers	14.51
Nail, tacking, shaping and joining mach ops (wood)	13.89
Extruding and forming machine operators	10.98
Machine feeders and offbearers	10.48
Other precision and craft workers	10.43
Construction laborers	9.76
Railroad brake, coupler, and switch operators	9.62
Helpers, constructions	9.56
Laborers, freight, stock, and material handlers, n.e.c.	9.21
Stevedores and misc. material moving occupations	9.18
Metal platers	9.06
Food preparation workers	8.91
Helpers, surveyors	8.58
Rollers, roll hands, and finishers of metal	8.21
Insulation workers	8.04
Mechanics and repairers, n.e.c.	7.91
Machine operators, n.e.c.	7.69
Shoemaking machine operators	7.61
Forge and hammer operators	7.61
Other metal and plastic workers	7.41
Machinery maintenance occupations	7.31
Food roasting and baking machine operators	7.18
Grinding, abrading, buffing, and polishing workers	7.16
Panel B: Safest occupations	
Lawyers and judges	0.02
Writers and authors	0.02
Barbers	0.03
Real estate sales occupations	0.08
Computer software developers	0.09
Architects	0.09
Medical scientists	0.09
Mathematicians and statisticians	0.09
Physicians	0.10
Biological scientists	0.10
Librarians	0.11
Computer systems analysts and computer scientists	0.11
Chemical engineers	0.11
Economists, market and survey researchers	0.12
Civil engineers	0.13
Fire fighting, fire prevention, and fire inspection occs	0.13
Dental laboratory and medical applicance technicians	0.14
Physicists and astronomists	0.15
Proofreaders	0.15
Electrical engineers	0.16
Accountants and auditors	0.17
Library assistants	0.17
Aerospace engineers	0.18
Mechanical engineers	0.18
Petroleum, mining, and geological engineers	0.20
Metallurgical and materials engineers	0.20