# Toxic Emissions from Statutory Cost Shocks

Davidmac Olisa Ekeocha[a,*]

[a] *University of Liverpool, Management School, Chatham Street, L69 7ZH, Liverpool, United Kingdom*

**Abstract**

This study investigates the intersection of labour policies and environmental sustainability, focusing on the unintended environmental consequences of minimum wage hikes within U.S. manufacturing industries. Using a staggered difference-in-differences framework and detailed facility-level data from the U.S. Environmental Protection Agency's Toxic Release Inventory, I examine how higher labour costs influence toxic emissions intensity. The findings reveal that a $0.89 increase in the hourly minimum wage leads to a 9.68-pound increase in toxic releases per $100 million units of output, with effects peaking at 22 pounds two years post-implementation. High-emission industries, such as chemicals and food production, are disproportionately impacted, primarily through air emissions from point and fugitive sources. The mechanism analysis supports the crowding-out hypothesis, demonstrating that higher labour costs reduce firms' investments in pollution abatement activities at production sources, including effective operating practices and training, improved material handling, and enhanced loading and transfer procedures. However, these practices serve as mitigation strategies to effectively counteract these adverse effects amid higher minimum wage hikes. The findings have broad implications for global labour markets and international environmental policy, emphasizing the need for integrated approaches that align wage reforms with sustainable industrial practices. As minimum wage policies are adopted and debated across diverse economic contexts, this study underscores the importance of complementary regulatory frameworks to mitigate environmental trade-offs and promote equitable, sustainable development on a global scale.

*Keywords:* Minimum Wage Policy, Toxic Releases, Manufacturing Emissions, Pollution Abatement, Environmental Externalities

## 1. Introduction

The effects of raising the minimum wage (MW) have garnered interest in the literature, reaching mixed conclusions for employment given assumed labour market conditions. For perfect competition, some studies have recorded disemployment effects of an MW raise on low-wage workers (Stigler, 1946; Hamermesh, 1982; Neumark and Wascher, 1992; Brown, 1999; Machin and Wilson, 2004; Neumark and Wascher, 2000; Borjas and Van Ours, 2010), whereas in monopsonistic markets, limited or a sharp null employment effect is documented (Lester, 1960; Card and Krueger, 1993, 2000; Aaronson et al., 2018; Cengiz et al., 2019; Wong, 2019; Dustmann et al., 2022). Other studies have recorded heterogeneous employment effects (Okudaira et al., 2019; Medrano-Adán and Salas-Fumás, 2023; Meer and Tajali, 2023; Gregory and Zierahn, 2022).

*Corresponding author
*Email address:* davidmac.ekeocha@liverpool.ac.uk (Davidmac Olisa Ekeocha)

On the other hand, the symmetry between raising MW and labour costs or wages of low-wage workers is well established (Medrano-Adán and Salas-Fumás, 2023; Clemens and Strain, 2023). Career progressions and high labour demand, higher job/worker effort and labour productivity, especially for incumbent workers in the $40th$ percentile of the wage distribution relative to workers in higher percentiles, largely drive the increase in wages of low-wage workers (Riley and Bondibene, 2017; Kim and Jang, 2019; Wong, 2019; Baek et al., 2021; Zhao and Sun, 2021; Seok and You, 2022; Ku, 2022; Coviello et al., 2022; Alexandre et al., 2022). They argued that firms' adjustments in total factor productivity, lower hiring and layoff and monitoring incentive explain the increased labour productivity, and that the increase in worker effort can offset about 50% of projected rise in labour cost. Furthermore, Harasztosi and Lindner (2019) argued that the cost-effect of raising MW is not only borne by employers and workers, but that firms tend to pass some of these burdens to consumers via higher prices.

Interestingly, the question regarding the existence of other pathways through which firms pass-through the burdens of higher-cost-induced MW, is still nascent. Thus, this paper addresses three key questions: $(i)$ How do firms respond (in terms of total toxic releases per $100 million units of output) to exogenous shocks, such as those driven by the minimum wage policy? $(ii)$ Are these responses heterogeneous across cohorts and type of manufacturing industries? $(iii)$ What are the transmission mechanisms of these responses? These studies focused on Chinese manufacturing firms to document higher pollution emission intensity induced by a MW raise (Li et al., 2023; Zhang et al., 2023). They argued that this effect is more prominent in financially constrained firms, such that the labour cost pass-through of MW, shifts firms energy usage towards cost-effective but crude energy sources, as well as reduced pollution abatement inputs and declining green innovation in their production functions. Albeit these studies used border-county design, they identified their effect using endogenous changes in MW, possibly indexed to inflation, thereby masking their causal claims of rising pollution emissions intensity. Hence, their results are indeed not causal, as it is not clear whether the documented pollution responses are due to an increase in MW or inflation.

However, using a natural experiment, this study leverages state-level exogenous changes in MW over time and administrative plant-level toxic emissions data (including air, water and land releases), from the environmental protection agency (EPA), to examine toxic responses of manufacturing firms to the MW policy, in the United States (US). The evidence on the environmental consequences of labour market shocks is particularly important for better health, environmental and labour market policy designs. Shapiro and Walker (2018) developed a model to historically explain the fall in the US pollution emissions in the manufacturing sector, and revealed several findings, including outsourcing production of pollution-intensive goods to other countries, like China and Mexico; use of pollution tax regulations would lead to increased investment in effective abatement technologies; and rising labour productivity decreases pollution intensity, thus decreasing pollution emissions.

Two hypotheses exist on possible transmission mechanisms of environmental consequences of raising MW: the factor substitution and crowding out effect hypotheses (Zhang et al., 2023). The factor substitution or labour-technology mix hypothesis argues for reductions in firms pollution emissions intensity. To maximize profits amid rising labour costs due to a raised MW floor, firms adjust their factor inputs by switching to automated production processes, from labour-intensive manual processes. Thus, replacing manual labour with machines and technologies, and increasing capital per worker while prioritizing resource allocations toward improving production functions through research (Harasztosi and Lindner, 2019; Hau et al., 2020; Geng et al., 2022; Dai and Qiu, 2023; Li et al., 2020). This will further increase labour productivity and total factor

productivity (Riley and Bondibene, 2017). Consequently, raising MW will cause firms to use efficient capital intensive methods, reducing energy intensity and ultimately decreasing emissions per unit of output. [1] Conversely, the crowding-out effect hypothesis argues in favour of increased firms' pollution emission intensity. These studies have evinced that this effect is attributed to the declining pressure on firms' profitability and heavier financial constraints resulting from wage hikes (Draca et al., 2011; Bell and Machin, 2018; Du et al., 2022). Consequently, constrained financial resources limit firms' investment in pollution abatement activities (as they focus on core production), leading to reduced pollution removal and higher emission intensity. [2] Therefore, to understand how labour-market shocks translate to environmental consequences, becomes an empirical exercise.

To document the causal effect of raising MW on total toxic release intensity, I use the Sun and Abraham (2021) staggered difference-in-differences estimator, exploiting copious and arguably exogenous changes in state-level MW ($\geq$ \$0.5 per hour) with clearly defined before- and after-periods. I exploit increases in Arkansas, California, Delaware, Maine, Massachusetts, Maryland, Michigan, Minnesota, Nebraska, New Jersey, New York, South Dakota and West Virginia, in 2014, 2015 and 2017. Hereafter, the treated states. I match each treated state to a set of adjacent control states that never implemented any MW policy from $2012-2017$, similar to Gopalan et al. (2021). I further restrict the sample to border-counties (Dube et al., 2010). The identifying assumption is that, absent any MW policy, economic conditions in adjacent cross-border counties would have evolved in parallel. Given this assumption, I show that the pre-treatment trends between the treated and control states are similar prior to the MW policy.

The main results indicate a statistically significant increase in total onsite toxic release intensity, following an exogenous rise in minimum wages. The estimated average treatment effect shows that for every \$0.89$c$ increase in hourly wages, there is an additional 9.68$lbs$ of toxic releases per \$100 million units of manufacturing output, reaching 22$lbs$ two years later. This effect persists across all cohorts, and is robust to controlling for facility-level characteristics, toxic chemical attributes, and common time-varying shocks. Narrowing in on the highest emitting industries—chemical, food, leather and allied products manufacturing—I find that the effect further increased to 22.88$lbs$. The top twenty emitted toxic chemical intensities, include nitrate compounds, ammonia, acetaldehyde, formaldehyde, methanol, hydrochloric acid, certain glycol ethers, hydrogen fluoride, ethylene, sulfuric acid, styrene, dimethyl phthalate, vinyl chloride, chloromethane, hydrogen cyanide, sodium nitrite, acrolein, n-butyl alcohol, barium, and barium compounds. This suggests that wage hikes may inadvertently intensify pollution, by increasing production costs and altering operational behaviour and processes, at manufacturing plants.

The mechanism analysis indicates that higher labor costs, driven by minimum wage increases, tend to elevate total toxic release intensity at facilities. This effect is mitigated by the implementation of source reduction operating practices and activities, such as improved material handling, and enhanced loading and transfer procedures, which effectively reduce overall pollution intensity. The analysis supports the crowding-out effect hypothesis, emphasizing the crucial role of these operational practices in counterbalancing the adverse environmental impacts of increased labor costs. Ultimately, integrating

[1] Similarly, the possiblity exists that firms may replace expensive factor inputs with cheaper but crude energy inputs that have higher pollution emission potentials, in their production process, which in turn increases energy and pollution emission intensities.

[2] In a different way, innovation is influenced by resource scarcity, leading to a preference for certain types of solutions. Technological advancement continues unabated, but resource constraints necessitate a balance between different types of solutions. Labour deficits, often caused by increases in the minimum wage, promote the development of labour-saving technologies, which can impede the progress of labour-intensive green technologies (Acemoglu, 2010). Firms often prioritize improvements in production efficiency over environmental considerations due to limited resources for innovation. For example, some environmentally friendly technologies, such as end-of-pipe treatments, require significant labour. This emphasis on efficient automation could divert resources away from the development of clean energy and waste management technologies, potentially resulting in increased pollution emissions intensity.

robust pollution control measures is essential for maintaining environmental performance despite higher labor costs.

The rest of the article is organized as follows: Section 2 provides the policy context of the study. Section 3 discusses the data and descriptive statistics. Section 4 discusses rising manufacturing industry costs due to exogenous state minimum wage changes. Section 5 discusses the effects on onsite toxic releases intensities. Section 6 discusses robustness exercises. Section 7 focuses on the heterogeneous effects. Section 8 investigates the potential mechanisms. Section 9 concludes with policy implications.

## 2. Policy Context

This section discusses the exogenous state minimum wage changes exploited in the covered sample period ($2011 - 2017$), for the causal identification.

### *2.1. Minimum Wage Changes across States*

About 27 states raised MW between 2011 and 2017. Except for Nevada, the majority of the changes in MW between $2011 - 2013$ are attributed to inflation. However, following the labour union protests in 2012 for higher MW, many states responded by instituting a one- or multi-phased large MW changes (Lathrop, 2021). Specifically, 13 states implemented a statutory MW raise of at least \$0.5 in 2014, 2015 and 2017. Pertinently, there was no raise in the federal MW, in the covered sample period. Table 10 of Appendix I presents the state-level changes in MW for the sample period.

### *2.2. Selecting the Treated and Control States*

The identification strategy focuses on the copious state-level MW changes. Particularly, I restrict the sample to MW changes that meet the following conditions: $(i)$ states with a large MW raise of $\geq \$0.5/hour$ in one year and had never raised their MW since 2012; $(ii)$ subsequent raises must either be equal to or greater than $\$0.5/hour$ in the post year, or the sum of post-multiphase raises (in any 2-years), must be equal or greater than the first initial raise for that state. These conditions ensure that the exploited MW changes capture the statutory MW policies, and not indexed to inflation. Thirteen (13) states meet these conditions. They include Arkansas, California, Delaware, Maine, Massachusetts, Maryland, Michigan, Minnesota, Nebraska, New Jersey, New York, South Dakota, and West Virginia. [3]

Table 1 provides a summary of the minimum wage adjustments in the sample. There are four increases of $\$0.75/hour$, four increases of $\$1.00/hour$, four increases of $\gg \$1.00/hour$ with a max of $\$1.85/hour$, and one increase of $\$0.5/hour$ in the sample. The average initial MW change is about $\$1.02/hour$ (7.6%). Following the first MW raise till the end of the covered period, there are seven post-initial total MW changes between $\$1.00 \leq \Delta MW \leq \$1.75$ per hour, four total post-initial MW changes between $\$2.00 \leq \Delta MW \leq \$2.50$ per hour, and two total post-initial MW changes between $\$3.00 \leq \Delta MW \leq \$3.35$ per hour. These have a total of post-initial MW average of $\$1.95/hour$, about (7.6%) total average MW changes, between 2011 and 2017. Further, the total percentage change in MW in the sample, for each treated state, range between 13.79% and 54.38%.

[3] New Jersey and South Dakota do not meet the second condition but are included in the treated sample. Hence, I explicitly control for US city-level average inflation in the model to net out any inflationary effects. Controlling for the year fixed effects in the model nets out this inflationary effect.

Table 1: Exogenous State-level MW Adjustments

| treated states | MW Δyear | MW Δamount $ | $\sum_1^{2\to3}$ ΔMW $ | total MW Δamount $ | total MW %Δ | start MW $ | end MW $ | control states | # of border counties (T) | # of border counties (C) |
|---|---|---|---|---|---|---|---|---|---|---|
| MN | 2014 | 1.85 | 1.50 | 3.35 | 54.38 | 6.16 | 9.51 | (IA, ND, WI) | 42 | 54 |
| MA | 2015 | 1.00 | 2.00 | 3.00 | 37.50 | 8.00 | 11.00 | (NH) | 8 | 6 |
| CA | 2014 | 1.00 | 1.50 | 2.50 | 31.25 | 8.00 | 10.50 | ($NV^p$) | 10 | 11 |
| NY | 2014 | 0.75 | 1.70 | 2.45 | 33.79 | 7.25 | 9.70 | (PA) | 27 | 16 |
| AR | 2015 | 1.25 | 1.00 | 2.25 | 36.00 | 6.25 | 8.50 | ($OK^p$, $TX^p$) | 19 | 12 |
| MD | 2015 | 1.00 | 1.00 | 2.00 | 27.59 | 7.25 | 9.25 | (PA, VA) | 21 | 39 |
| NE | 2015 | 0.75 | 1.00 | 1.75 | 24.14 | 7.25 | 9.00 | (IA, $KS^p$, WY) | 28 | 24 |
| ME | 2017 | 1.50 | 0.00 | 1.50 | 20.00 | 7.50 | 9.00 | (NH) | 5 | 7 |
| MI | 2014 | 0.75 | 0.75 | 1.50 | 20.27 | 7.40 | 8.90 | (IL, IN, WI) | 32 | 39 |
| WV | 2015 | 0.75 | 0.75 | 1.50 | 20.69 | 7.25 | 8.75 | ($KY^p$, PA, VA) | 32 | 28 |
| $SD^p$ | 2015 | 1.25 | 0.15 | 1.40 | 19.31 | 7.25 | 8.65 | (IA, ND, WY) | 27 | 19 |
| NJ | 2014 | 1.00 | 0.19 | 1.19 | 16.41 | 7.25 | 8.44 | (PA) | 16 | 13 |
| DE | 2014 | 0.50 | 0.50 | 1.00 | 13.79 | 7.25 | 8.25 | (PA) | 5 | 6 |

NOTES: This table summarizes the exogenous state-level MW changes from 2011 to 2017. There are thirteen (13) treated and (14) control states. The definition of treated and control states is given in sub-section 2.2. MW Δyear represents the year in which a treated state first raised its MW. MW Δamount $, corresponds to the first MW raised amount for that year. $\sum_1^{2\to3}$ ΔMW $, denotes the sum of any post-two-to-three-year MW changes after the first initial raise. Total MW Δamount $, corresponds to the total MW raised amount till the end of the sample. Total MW %Δ, corresponds to the total percentage change in MW till the end of the sample. Start (End) is the MW at the start (end) of the sample. Control states are the set of control states for each treated state. These states never raised MW between 2012 and 2017. # of border counties (T) is the number of counties in a treated state that border at least one county in a control state. And # of border counties (C) is the number of counties in a control state that border at least one county in a treated state. States with superscripts are not present in the POTWs sample.

Furthermore, I match each treated state to adjacent control states, that never raised their MW between 2012 and 2017, and follow Dube et al. (2010) and Gopalan et al. (2021) to limit the sample to border counties in treated and control states. Other recent papers have used similar identification strategy (Aaronson et al., 2018; Dube et al., 2019; Jardim et al., 2018; Zhang, 2019). The control states in the sample include Iowa, Illinois, Indiana, Kansas, Kentucky, North Dakota, New Hampshire, Nevada, Oklahoma, Pennsylvania, Texas, Virginia, Wisconsin, and Wyoming. [4] Table 1 shows that there are 13 treated and 14 control states in the sample. The last two columns further show that there are a total of 272 treated and 274 control border counties. Figures 1 and 2 show the geographical locations of the treated and control states and counties, respectively.

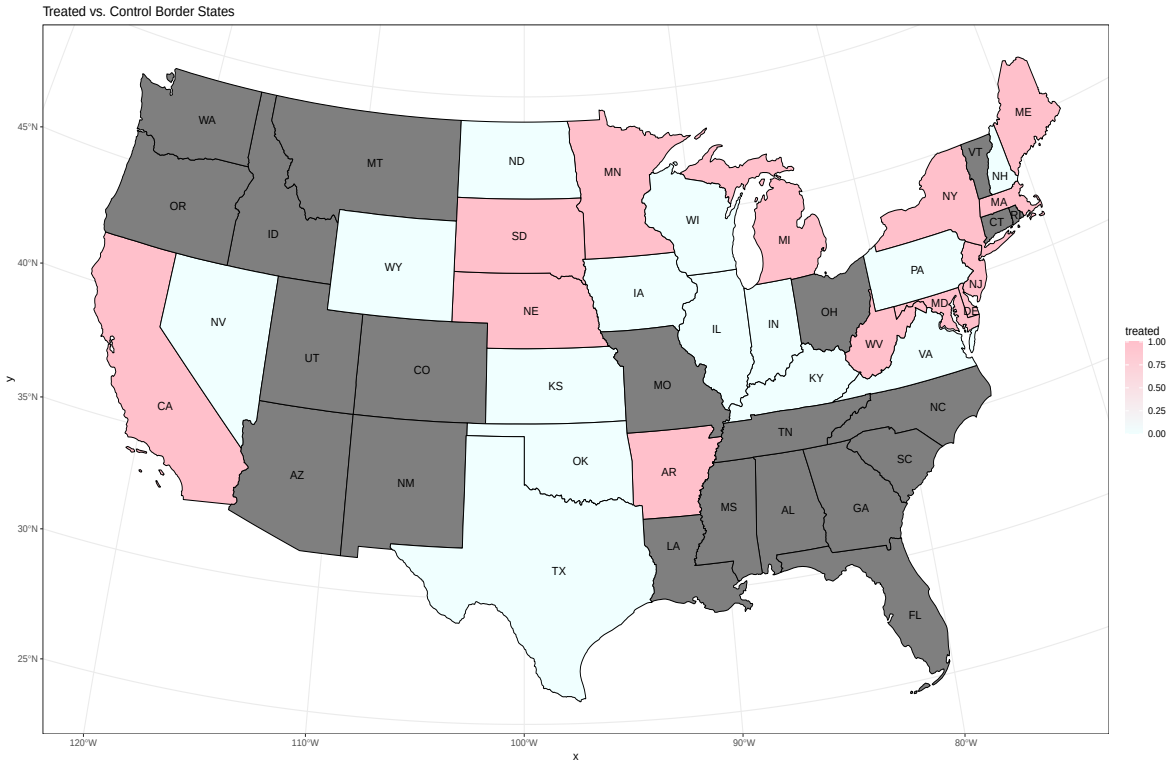



Figure 1: Map of Treated and Control States

[4] Importantly, Georgia, Idaho, New Mexico, North Carolina, and Utah are removed from the list of control states as they are not adjacent to any treated states.

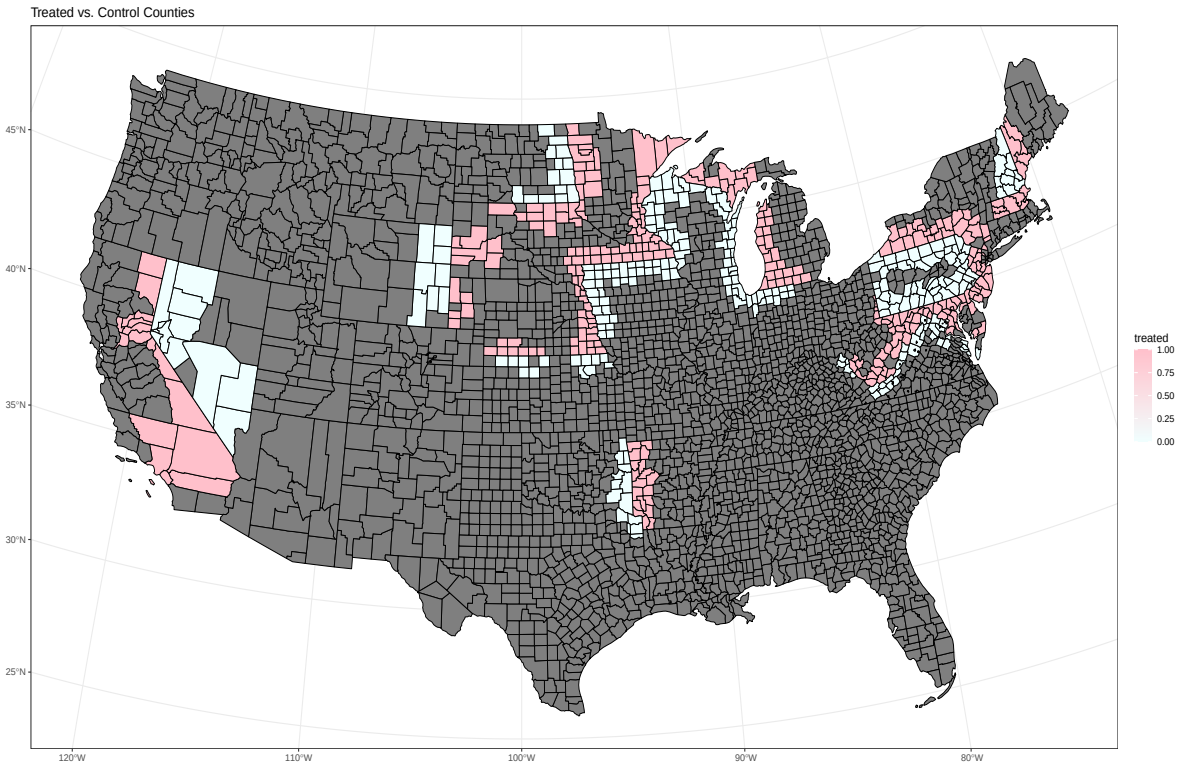



Figure 2: Map of Treated and Control Counties

Each treated border county is paired with a cross-border control county, described as the pair of the adjacent treated and control counties. The identifying assumption in a cross-border county pair is that the evolution of economic conditions for the pairs is symmetric and parallel, but the MW levels vary discontinuously at the border. To address the concern raised in Neumark et al. (2014) on the validity of border counties as counterfactuals, Figure 7 presents a comparison of economic conditions before the first initial year of the MW change. Along most of the observable pre-treatment variables, the trends appear to be statistically parallel between the treated and control border counties and states. [5]

## 3. The Data

For the empirical analysis, the novel data used come from five different sources, and combined with the linked administrative facility level Toxic Release Inventory (TRI) data, from the US Environmental Protection Agency (EPA).

### *3.1. Toxic Release Inventory Data*

I collect TRI-form-R data from EPA, which contains inventory of toxic chemical releases that are either manufactured, processed, otherwise used, and/or managed at private, state and federal industrial facilities across the US States. To file a TRI reporting form R, a facility must have at least ten full-time employees, and manufactures (including import) or processes more than 25,000 pounds, or otherwise uses more than 10,000 pounds of a TRI-listed chemical during a calendar year. TRI data reflect, among other things, quantities of chemicals managed by facilities as waste, including those quantities released into the environment (as air emissions, water and land pollution), treated, burned for energy, recycled, and transferred from

[5] Tables 11 and 12 of Appendix I present a comparison of the difference in means of the pre-treatment variables for the treated and control border counties, and states. The results show no significant difference in means for the treated and control border counties and states.

one facility to another for release or further management. It provides facility-level information based on 5-digit zip codes identifying the exact location of the facility within each city, county, and states in the US.

I collate onsite facility panel information, as well as offsite transfers, and Publicly Owned Treatment Works (POTWs) toxic chemical releases, and waste management practices. There are 167 different toxic chemical releases consistently reported by the same facilities in the sample, belonging to 213 different NAICS manufacturing industries. See Figure 21 of Appendix III for the distribution of NAICS manufacturing industries in the sample. [6]

### *3.2. Wage Data*

I use the industry-level wage data from the National Bureau of Economic Research-Centre for Economic Studies (NBER-CES). The NBER-CES data contains complete information on industry-level production workers and their wages, production workers' hours, and total payroll for manufacturing industries. Using this information I construct the industry-level production workers' wage per hour and wages per worker.

### *3.3. Other Industry and Macroeconomic Data*

The industry-level data from the NBER-CES and contains other variables including employment, total revenues, material costs, energy cost, output measured as value added, and total factor productivity, etc, for only manufacturing industries in the US.

Additionally, the macroeconomic data are at the county level, sourced from the Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labour Statistics (BLS), and include variables such as the average number of establishments, and industry ownership. The county-level gross domestic product is sourced from the Bureau of Economic Analysis (BEA). The inflation data is got from the BLS consumer price index historical dataset for all urban consumers.

### *3.4. Joining the Datasets and the Sample*

I begin by joining the US zip-code and county-level geographic shapefiles (by zip-codes) to the TRI data to get the corresponding FIPS codes. These were then used to join the BEA, BLS and QCEW data by year, FIPS and 6-digit NAICS codes. The resulting data were further merged to the NBER-CES dataset, by their NAICS codes. Finally, this merged data was then joined with the prepared US geographic adjacent county shapefile, that has information on county-level population, and county distance to a state border. I prepared these shapefiles in the spirit of Dube et al. (2010) and Gopalan et al. (2021), where each treated county or state is matched to at least one adjacent cross-border county or state, yielding cross-border county/state pairs. This final novel dataset is used for the empirical analysis of this paper.

From the merged dataset, I subset a panel sample of onsite facilities, as well as their transfers to offsite and POTWs locations. The onsite data sample size is $1,893,689$, and consists of 1276 manufacturing facilities, belonging to 213 NAICS codes (in 20 manufacturing industries), and a panel of 167 toxic chemicals. Figure 21 of Appendix III shows the distribution of these manufacturing industries, which reports that chemical, forging and stamping, primary metals, petroleum and coal

[6] These manufacturing industries are categorized into: Beverage and tobacco product, chemical, computer and electronic product, food, forging and stamping, furniture and related products, household appliances, leather and allied products, machinery, miscelleneous, non-metallic mineral product, paper, petroleum and coal products, plastics and rubber products, primary metal, printing and related support activities, textile mills, textile product mills, transportation equipment, and wood product manufacturing.

products, transportation equipment, and machinery manufacturing industries, are the most common in the sample. This is an administrative facility-level panel located in a 5-digit zip-codes, in both the treated (13) and adjacent control (14) border states. A total of 27 states and the number of cross-border counties are as described in section 2.2.

The offsite and POTWs samples are subsets of the onsite sample. The offsite panel sample size is $1,179,754$, and POTWs sample is $308,943$. The original panel of onsite facilities across time reduced to 680 and 236 in the offsite and POTWs samples, respectively. The number of toxic chemicals in the offsite and POTWs samples are 125 and 69, respectively. See Table 16 of Appendix II for the list of analysed chemicals, and Figure 10 for the list of the top and least emitted toxic chemicals. The number of NAICS industries in the offsite and POTWs samples are 171 and 101. Finally, there are 14 and 9 control states in the offsite and POTWs samples; 13 and 12 treated states in the offsite and POTWs samples, respectively (see Table 1). Importantly, the number of onsite treated and control states remained unchanged in the offsite sample. A total of 827 offsite facilities are located in 1056 zip-codes in 573 cities of 299 counties in 45 US states, whereas the 114 POTWs sites are found in 202 zip-codes in 123 cities of 63 US counties in 24 US states. [7]

### *3.5. Covariate Balancing and Descriptive Statistics*

Tables 11, and 12 of Appendix I show the results of the balance tests for the treated and control border counties, and states, respectively. It is clear that the pre-treatment covariates are well balanced between the treated and control border counties, and states. Additionally, Table 13 of the same Appendix reports the summary statistics for manufacturing industry costs, employment and hours, and outputs and labour productivity, toxic release intensities, essential county-level macroeconomic indicators and facility-level covariates.

The average county population is approximately $693,000$, with a per capita gross domestic product of $\$48,000$ and a city-wide consumer price index of \$235. The are 5 industry establishments annually, and an average of $44,000$ people employed in manufacturing industries. Specifically, there are a total of $31,000$ manufacturing industry workers focused on production activities, grossing around 65 million hours annually.

The average total payroll in manufacturing industries is approximately \$3 billion, and production workers wages per hour is about \$27. Notice that the standard deviation is around \$7, with a minimum of \$12 and a maximum of \$54. This indicates that manufacturing industry workers in the sample are paid above the federal minimum wage of \$7.25. The average total cost of materials is around \$61 billion. As a result, the average total output is around \$18 billion in value added, and approximately $\$3,000$ worth of output produced every hour, with a labour productivity of around $\$4,000$. The average profit is about \$14.8 billion.

All the manufacturing industry facilities in the sample are privately owned. Around 7% import chemicals, and 24% produced their own chemicals at the facility. There are a total of 167 toxic chemicals in the dataset (see Table 16 in Appendix I). On average, the maximum number of these chemicals at a facility, at any given time, is four. About a quarter of these industries use these chemicals for ancillary purposes, 32% use them as a formulation component and very few use them as a

[7] The offsite states include Alabama, Arkansas, Arizona, California, Colorado, Connecticut, Delaware, Florida, Georgia, Iowa, Idaho, Illinois, Indiana, Kansas, Kentucky, Louisiana, Massachussetts, Maryland, Maine, Michigan, Minnesota, Missouri, North Carolina, North Dakota, Nebraska, New Hampshire, New Jersey, New Mexico, Nevada, New York, Ohio, Okhlahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota,Tennesse, Texas, Utah, Virginia, Vermont, Wisconsin, and West Virginia. The POTWs states include Arkansas, California, District of Columbia, Delaware, Iowa, Illinois, Indiana, Massachussetts, Maryland, Maine, Michigan, Minnesota, North Dakota, Nebraska, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Texas, Virginia, Wisconsin, West Virginia, and Wyoming.

manufacturing aid. The production ratio or activity index is 2%, suggesting that changes in toxic chemical releases are due to operational changes. [8]

The average total releases intensity (per $100 million dollars units of output) is around 88 pounds (lbs). This is the sum of the weights of the intensities of total air emissions (from point and fugitive sources)—60$lbs$, surface water discharge—20$lbs$, and land releases—8$lbs$. Note that total number of receiving streams for toxic release appear to be near zero, suggesting an insufficient number of streams to dispose toxic chemicals. Additionally, land releases intensity is the sum of the weights of the intensities of total underground, landfills, releases to-land treatment (used for agricultural fertilization), surface impoundment, and other land releases. They largely constitute waste management activities, and characterised by very low percentages. Finally, the average total releases intensity from catastrophic events, such as fire, flood, industrial accidents, etc, is around 4$lbs$. Notice their wide standard deviations, suggesting heterogeneous dynamics in the composition of the total releases intensities in manufacturing industries, evident in the zero minimum and large positive maximum values.

### *3.6. Trends in Toxic Releases Intensities*

Figure 3 illustrates the evolution of total onsite toxic release intensities by treatment status, grouped by treatment dates. Panels A-C depict the pre-treatment evolution for the states treated in 2014, 2015, and 2017, compared to the control group that remained relatively unchanged in panels A and B.

Panel A shows a largely parallel pre-treatment trend in toxic emission intensity for the 2014 cohort. There is a significant increase to 200 pounds in 2014, followed by a decline through 2016, and then another rise in 2017. Panel B displays similar patterns for the 2015 cohort, with larger relative magnitudes. This cohort experiences an even higher increase in toxic release intensity in 2017, two years post-treatment.

Finally, Panel C indicates parallel pre-treatment trends for the 2017 cohort until 2017, when the treated group shows a smaller increase in toxic release intensity. These increases in toxic release intensities for the treated groups led to this investigation, aiming to determine the impact of changes in state-level minimum wages.

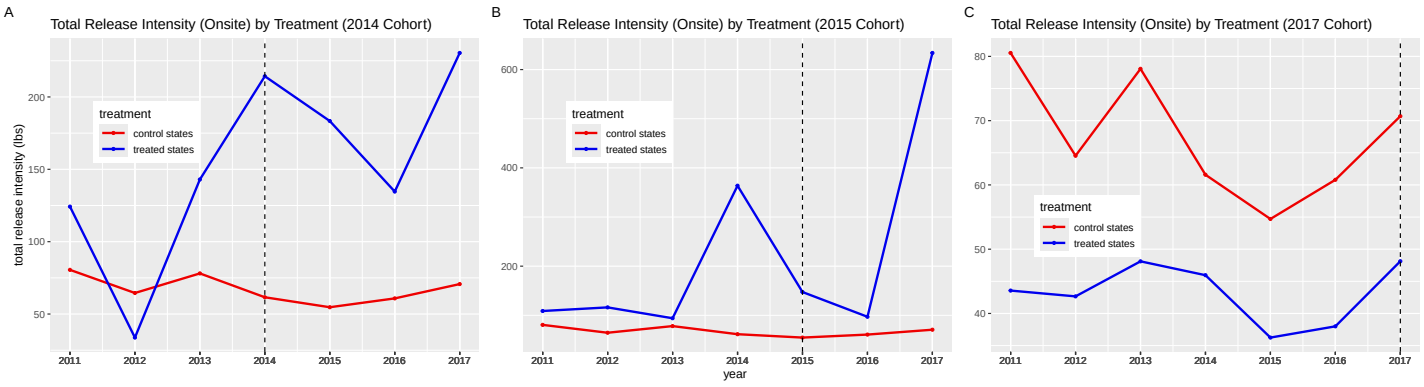



Figure 3: Trends in Release Intensities by Treatment Status and Cohorts

[8] The production ratio or activity index reflects the change in production levels at a facility relative to the prior year. It measures the extent to which changes in toxic chemical releases are due to changes in production or other activity levels, rather than improvements or deteriorations in environmental practices. A ratio greater than 1 indicates increased production, while less than 1 signals decreased production. This helps in understanding whether variations in toxic releases are due to operational changes or external factors.

## 4. Rising Industry Costs

The empirical analyses begin by documenting the effect of exogenous increases in statutory minimum wage on industry costs, such as labour costs (including hourly wages, and total payroll), and material costs. [9] The baseline model is given by:

$$C_{i,cp,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \delta_h + \zeta_{cp,t} + \epsilon_{i,cp,t}, \tag{1}$$

where $C_{i,cp,t}$ is the vector of industry costs (hourly wages, total payroll and material costs) of manufacturing industry $i$, in cross-border county pairs $cp$, in the year, $t$. $Treated^{e}_{s,t} = \mathbf{1}[t - G_{s,t}]$, is unity for the treated states that are $e$-periods away from the vector of initial treatment dates $G_{s,t} \in \{2014, 2015, 2017\}$, and zero for the control states. [10] $X_{v,h,t-1}$ denotes lagged values of county-level GDP per capita, annual average establishments, and city-level inflation (Gopalan et al., 2021; Dube et al., 2010; Clemens, 2019). $F_{f,t}$ contains facility-level dummies on industry ownership.

I control for year $\lambda_t$, and county $\delta_h$, fixed effects, to account for time-varying factors and within county differences that may affect the MW policy, such as inflation, within county differences and political climate. $\zeta_{cp,t}$ is the cross-border county pair by year fixed effects to control for the evolution of time-varying common shocks in cross-border county pairs, such as changes in political administrations and national economic conditions. Standard errors are clustered at the state level, as changes in MW may be correlated within a state.

Table 2: Effect of the MW Policy on Industry Costs

| Industry costs | Hourly wage ($) | | Total payroll (log) | | Material cost (log) | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| $Treated^{e}$ | 0.397 | 0.892* | -0.015 | 0.044* | -0.032 | 0.130* |
| | (0.358) | (0.452) | (0.031) | (0.025) | (0.113) | (0.069) |
| cohort 2014 | 0.582 | 1.200 | -0.030 | 0.004 | -0.081 | 0.187* |
| | (0.523) | (0.706) | (0.032) | (0.039) | (0.174) | (0.098) |
| cohort 2015 | 0.091 | 0.390* | 0.010 | 0.115*** | 0.051 | 0.036 |
| | (0.260) | (0.217) | (0.062) | (0.014) | (0.093) | (0.076) |
| cohort 2017 | -0.265 | -0.205 | -0.113*** | -0.643*** | 0.024 | -0.343*** |
| | (0.226) | (0.323) | (0.019) | (0.126) | (0.031) | (0.100) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| county FE | Yes | Yes | Yes | Yes | Yes | Yes |
| border-county pair × year FEs | No | Yes | No | Yes | No | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.581 | 0.624 | 0.404 | 0.440 | 0.577 | 0.619 |
| Baseline Mean | 26.56 | 26.56 | 2962.68 | 2962.68 | 61328.05 | 61328.05 |

NOTES: These results are obtained from estimating model 1. Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

The average treatment effect on the treated (ATT) is captured by $\beta$, which is the difference in the average effect of raising the MW floor on manufacturing industry costs, in treated counties relative to adjacent control counties. The effects measured by

[9] The empirical analyses examining the effect of statutory minimum wage on manufacturing industry employments, workers' hours and worker mobility spillovers, outputs and labour productivity, and industry profits, are reported in the online supplementary material. These analyses and heterogeneous characterizations have implications on the transmission mechanisms discussed in Section 8.

[10] To rule out any possible treatment selection, I estimate this equation at both the county and state level: $Treated^{e}_{s,t} = \beta Z_{f,cp,t} + \lambda_t + \delta_h + \zeta_{cp,t} + \epsilon_{f,cp,t}$. Where $Z_{f,cp,t}$ is the vector of facilities by county-pair covariates (including lagged values), and $\beta$ is the vector of coefficients. Albeit the year fixed effects $\lambda_t$, nets out any inflationary effects, city-level inflation is explicitly controlled for in the model. The results (reported in Table 14) of Appendix I, show no significant treatment selection effects in the following covariates: lagged values of county-level gross domestic product (GDP), GDP per capita, annual average establishments; inflation; average number of establishments, industry ownership and coverage.

$\beta$ are recovered using the Sun and Abraham (2021) staggered difference-in-differences (DiD) estimator, an improvement over the TWFE estimator. I report the decomposition results from De Chaisemartin and d'Haultfoeuille (2020), investigating possible negative weights in the TWFE estimator when the treatment assignment is staggered. Albeit the results from both estimators are largely similar, the analyses in this paper are guided by the coefficients of the staggered DiD estimator.

The results on industry costs are reported in Table 2. I find that a higher MW policy increases manufacturing industry wages (labour costs) in treated counties relative to adjacent control counties. Manufacturing industry wages per hour rose by \$0.89*c*. This result is almost twice as strong as that documented in Gopalan et al. (2021), for the industry-wide effect on hourly wages of \$0.48*c*. This suggests that the manufacturing industry is strongly affected by the MW policy relative to other industries in the US. Hence, the bite in industry costs due to a higher MW floor is higher in the manufacturing industry compared to others. I further document an increase in total payroll, by 4.4 percentage points (ppts), as well as an increase in cost of materials in manufacturing industries, by 13ppts. These effects are detected after controlling for time-varying common shocks at border counties. These results are robust, even at different lower levels of clustering the standard errors, in Table 15 of Appendix I.

The cohorts specific effects reveal that except for the 2015 cohort where labour cost rose by \$0.38*c*, it is mute for both the 2014 and 2017 cohorts. This suggests that the bite of raising MW is strongest for states that first raised their MW floor in 2015. Similarly, I find an increase of 12%, in total payroll for the same cohort, and an increase of 19%, in material costs for the 2014 cohort. However, I find a declining effect in total payroll and material cost for the 2017 cohort. Maine is the only state in this cohort. The disemployment effect discussed for the 2017 cohort, in the online supplementary material, explains these declining effects.

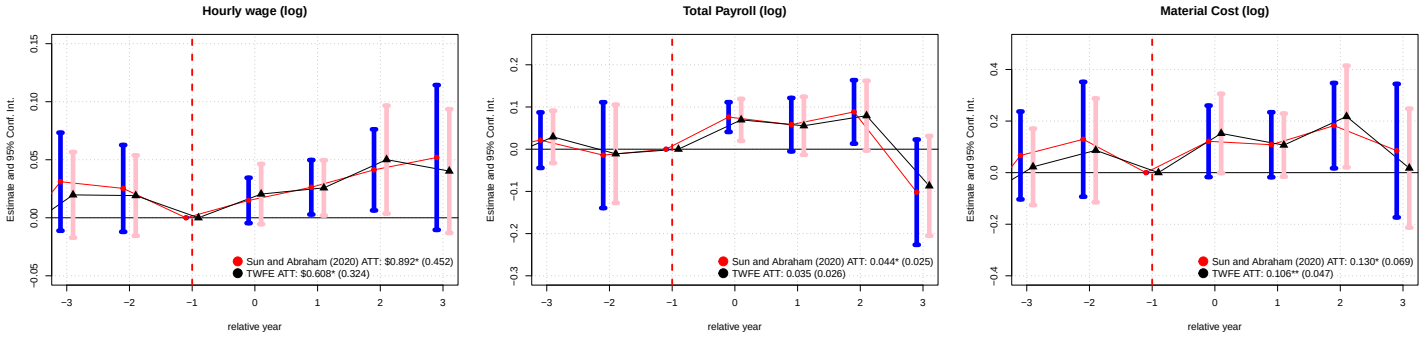



Figure 4: Manufacturing Industry Costs

NOTES: The event study model of equation 1 is $C_{i,cp,t} = \sum_{e=-3,e\neq-1}^{3} \beta Treated_{s,t}^{e} = \mathbf{1}[t - G_{s,t}] + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \delta_h + \zeta_{cp,t} + \epsilon_{i,cp,t}$. Standard errors are clustered at the state level. de Chaisemartin and D'Haultfoeuille Decomposition: $\sum dCDH_{ATTs}^{weights(+)} = 1$ and $\sum dCDH_{ATTs}^{weights(-)} = 0$.

Figure 4 reports the dynamic effects. It shows increases in hourly wages in the first and second year following an MW policy. Moreover, I find instantaneous increases in the manufacturing industry's total payrolls and cost of materials, persisting up to three years after initially raising MW. There is no evidence of significant pre-trends. The timing and size of the effect are consistent with my data and setting.

The heterogeneous effects in Figure 9 of Appendix I, illustrates that the impact on manufacturing industry labour costs, is more pronounced in high-skilled workers compared to low-skilled workers. The figure shows an immediate increase in hourly

wages. While this increase dissipates from the first to the third year of post-treatment for low-skilled workers, it persists for up to three years later, for high-skilled workers. Similarly, total payroll for high-skilled workers increases, whereas it substantially declines for low-skilled workers in the second year of post-treatment. These findings indicate that the labour cost effect of raising the minimum wage is stronger for high-skilled workers in manufacturing industries, which suggests a spillover effect. [11] Furthermore, the labour cost burden is dominated in high-profit and capital-intensive industries relative to low-profit and labour-intensive industries, where there is declining labour cost throughout the post-treatment periods.

## 5. Onsite Toxic Release Intensity

To address the first research question, I begin by estimating the effect of an exogenous increase in statutory minimum wage on total onsite toxic release intensity, at manufacturing industry facilities. The main model is given by:

$$P_{f,cp,c,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \tag{2}$$

where $P_{f,cp,c,t}$ is the total onsite release intensity at manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical use $c$, in the year $t$. $Treated^{e}_{s,t} = \mathbf{1}[t - G_{s,t}]$ is unity for the treated states that are $e$-periods away from the vector of initial treatment dates $G_{s,t}$, and zero for the control states. $X_{v,h,t-1}$ denotes lagged values of county-level GDP per capita, annual average establishments, and city-level inflation (Gopalan et al., 2021; Dube et al., 2010; Clemens, 2019). $F_{f,t}$ contains facility-level variables, including maximum number of toxic chemicals in a facility at any point in time, production/activity ratio index of the facility, dummies of industry ownership, and toxic chemical attributes—whether the chemical was: produced at or imported to the facility, used as a formulation or article component, used as a manufacturing aid or for ancillary purposes. Additionally, I control for environmental policy variables such as the Clean Air Act (CAA) of 1970 and as amended in 1990 to capture Hazardous Air Pollutants (HAPs), proxied by the dummy of CAA and HAPs regulated chemicals, and the Toxic Substances Control Act (TSCA) of 1976 proxied by the dummy of persistent bio-accumulative toxic (PBT) chemicals.

I control for facility-level fixed effect $\gamma_f$, to account for within facility-level differences in the management of toxic release intensities at the facility. And $\eta_{c,t}$, is the toxic chemical linear trends which controls for the evolution of common time-varying shocks, that may affect the nature of chemical usage at manufacturing industry facilities. $\theta_{cp,t}$ is the border-county pair by year fixed effects to control for common time-varying shocks that affect border-counties, such as change in county governments and national economic conditions. Finally $\varepsilon_{f,cp,c,t}$ is the orthogonal idiosyncratic error term. I employ a multi-level clustering of the standard errors at the chemical use, industry, and state levels, because changes in MW may be correlated within a state, within manufacturing industries in the state, and in the nature of toxic chemical usage in the industry.

[11] Notably, low-skilled workers, defined as those below the 30th percentile of the wage distribution, and comprising 18.2% of the workers, further demonstrate that the manufacturing industry workforce is skewed towards high-skilled workers (see Figure 8 of Appendix I).

Table 3: Effect of the MW policy on Total Onsite Toxic Releases Intensity

| Total release intensity (log) | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $Treated^e$ | 0.020 | 0.120** | 0.108** | 0.110*** |
| | (0.110) | (0.052) | (0.049) | (0.041) |
| cohort 2014 | -0.154 | 0.077 | 0.090** | 0.100** |
| | (0.120) | (0.055) | (0.044) | (0.048) |
| cohort 2015 | 0.315* | 0.191*** | 0.139* | 0.126** |
| | (0.172) | (0.073) | (0.077) | (0.050) |
| cohort 2017 | -0.502** | 0.030 | 0.223** | 0.238** |
| | (0.200) | (0.061) | (0.090) | (0.106) |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | No | Yes | Yes | Yes |
| toxic chemical × year FEs | No | No | Yes | Yes |
| border-county pair × year FEs | No | No | No | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.169 | 0.520 | 0.720 | 0.726 |
| Baseline Mean | 87.99 | 87.99 | 87.99 | 87.99 |

NOTES: These results are obtained from estimating model 2. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

The overall and cohort-specific ATT is captured by $\beta$, which is the difference in the average effect of raising the MW floor on total onsite release intensity, at manufacturing industry facilities in treated counties relative to adjacent control counties. The results on total onsite release intensity are reported in Table 3. It shows that a higher MW policy increases total onsite release per \$100 million units of manufacturing industry output by 11ppts, across all cohorts. This translates to a $0.11 \cdot 87.99 = 9.68 lbs$ additional increase in total onsite release intensity, for every $\$0.89 c/hr$ increase in the wages of manufacturing industry workers. This effect persists even after controlling for time-varying common shocks, that may affect border-counties and the nature of toxic chemical usage at manufacturing facilities. Figure 12 of Appendix II, shows the list of the top twenty toxic chemical release intensities, which includes nitrate compounds, ammonia, acetaldehyde, formaldehyde, methanol, hydrochloric acid, certain glycol ethers, hydrogen fluoride, ethylene, sulfuric acid, styrene, dimethyl phthalate, vinyl chloride, chloromethane, hydrogen cyanide, sodium nitrite, acrolein, n-butyl alcohol, barium, and barium compounds.

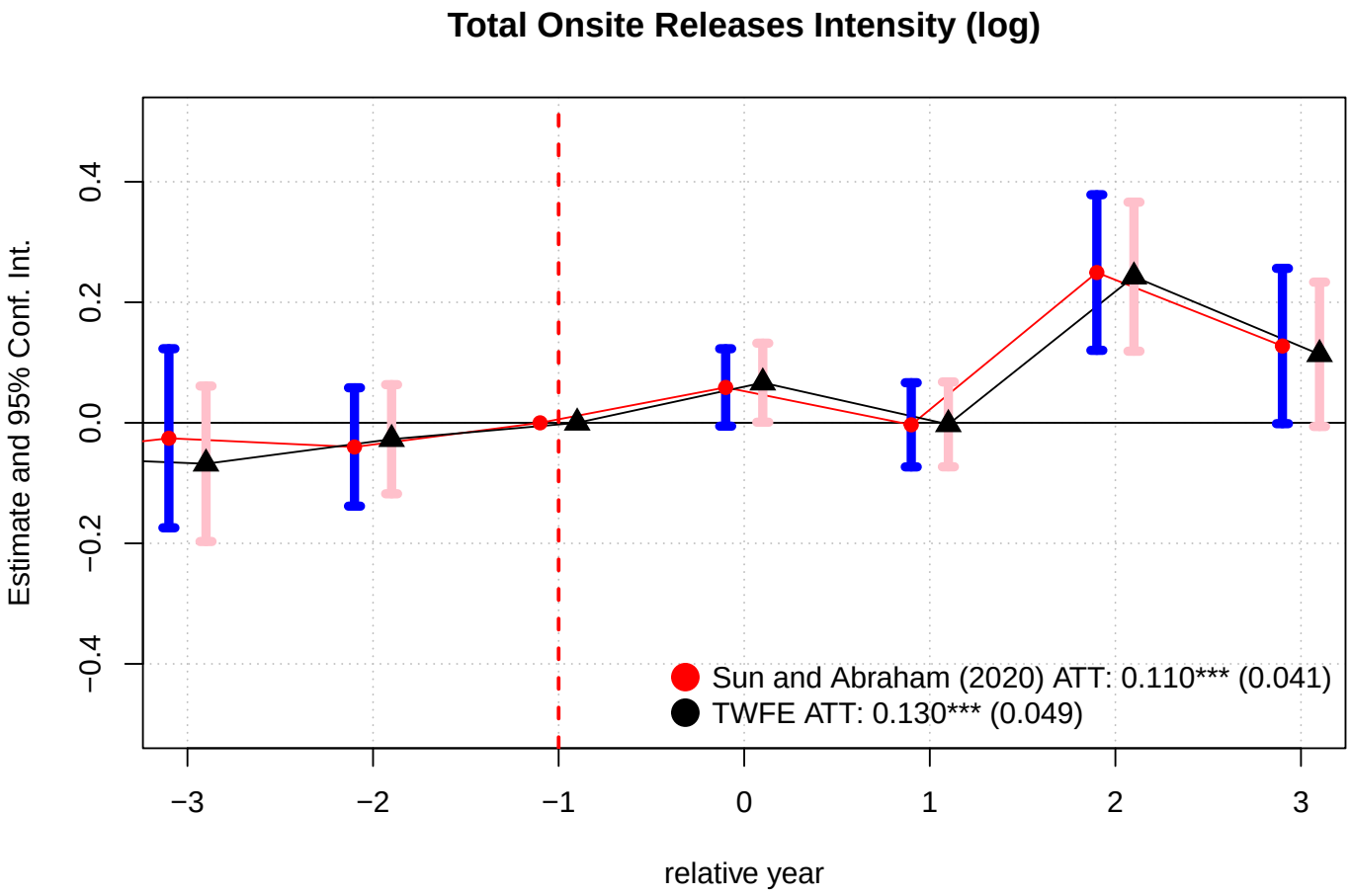



Figure 5: Total Onsite Releases Intensity

NOTES: The event study model of equation 2 is $P_{f,cp,c,t} = \sum_{e=-3, e\neq -1}^{3} \beta Treated_{s,t}^{e} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}$. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. The test for the presence of pre-trends shows and F-statistic of 1.195 (0.550), p-value (in parentheses) using F-Statistic ($\chi^2$) : $\sum_{-3}^{-2} \beta_e = 0$. de Chaisemartin and D'Haultfoeuille Decomposition: $\sum dCDH_{ATTs}^{weights(+)} = 1$ and $\sum dCDH_{ATTs}^{weights(-)} = 0$.

Moreover, Figure 5 shows an instantaneous increase of $6ppts$ in total onsite release intensity, reaching $25ppts$ two years later (about $22lbs$), and then receded to $12ppts$ in the third year. There is no significant evidence of pre-trends. Notably, the alternative TWFE estimator show consistent and similar effects.

Economic theory suggests that economic growth patterns are correlated with pollutant emissions, with a turning point at higher economic growth (Grossman and Krueger, 1995; Shapiro and Walker, 2018). I show in Figure 26 of Appendix III, the differential impact of higher MW on onsite total release intensity, in high v. low gross domestic product (GDP) counties. Where $H_{h,s,t} \in \{1, 0\}$, is a dummy that is unity for a high GDP of county $h$, in state $s$, in the year $t$, and 0 otherwise (i.e., low GDP). High GDP is defined as those counties with total pre-treatment GDP above the median quantile, of the GDP distribution of all counties. Consistent with theory, the results show limited evidence of a differential decrease in total onsite toxic release intensity, for high GDP counties. Conversely, low GDP counties witnessed a significant increase, emerging in the second through the third year of post-treatment. Example of the top ten of these toxic chemical releases, as Figure 11 shows, include, nitrate compounds, ammonia, acetaldehyde, formaldehyde, methanol, hydrogen fluoride, hydrochloric acid, sulfuric acid, barium compounds, and certain glycol ethers.

*5.1. Air Emissions Intensity*

Here, I trace the source of the increase in total onsite toxic release intensity, by estimating the effect of raising MW on total onsite toxic air emission intensity. The model is given by:

$$A_{f,cp,c,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \tag{3}$$

where $A_{f,cp,c,t}$ is the total onsite air emission intensity from manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical $c$, in the year $t$.

Total onsite air emission intensity is the sum of point/stack air emissions and fugitive air emissions intensities. Point air emissions usually involve the release of pollutants or substances into the atmosphere from industrial or commercial sources, through a designated stack, chimney, or venting mechanism. These emissions occur as a result of combustion processes, industrial operations, or other activities that involve the burning, processing, or handling of materials. Stack emissions are typically regulated and monitored to ensure compliance with environmental regulations and standards. Fugitive air emissions on the other hand, refer to the release of pollutants or substances into the atmosphere from various industrial, commercial, or other sources that are not captured by a stack/point, duct, or other venting mechanism. These emissions typically occur during the handling, storage, processing, or transportation of materials, and can originate from leaks, spills, evaporation, or other unintended releases from wear and tear of equipments. Examples of such emitted air pollutants, as shown in Figure 13, include benzene, methyl methacrylate, trichloroethylene, and all the aforementioned toxic chemicals, except sodium nitrate, and barium. Monitoring and controlling stack emissions are critical for minimizing air pollution, protecting public health, and reducing environmental impacts.

Table 4: Effect of the MW policy on Air Emissions Intensity

| | Total | | Sources | |
|---|---|---|---|---|
| Air emissions intensity (log) | 1 | 2 | Point | Fugitive |
| $Treated^e$ | 0.101** | 0.092*** | 0.043* | 0.066** |
| | (0.048) | (0.032) | (0.025) | (0.030) |
| cohort 2014 | 0.100* | 0.121*** | 0.113*** | -0.001 |
| | (0.053) | (0.046) | (0.041) | (0.037) |
| cohort 2015 | 0.103 | 0.043 | -0.074* | 0.176*** |
| | (0.067) | (0.044) | (0.042) | (0.053) |
| cohort 2017 | -0.045 | 0.118 | 0.055 | 0.157* |
| | (0.064) | (0.096) | (0.089) | (0.086) |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | No | Yes | Yes | Yes |
| border-county pair × year FEs | No | Yes | Yes | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.522 | 0.745 | 0.718 | 0.669 |
| Baseline Mean | 60.02 | 60.02 | 49.07 | 10.95 |

NOTES: These results are obtained from estimating model 3. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

The parameter of interest is $\beta$, which measures the overall and cohort-specific ATTs of the MW policy on air emission intensity, at manufacturing industry facilities. The results are presented in Table 4. I find an increase of $9.2 ppts$ in total air emissions intensity in treated counties relative to adjacent control counties. Albeit the reported effect size is smaller than the size of the effect in Zhang et al. (2023), it is similar to their conclusions for Chinese manufacturing industries. The focus on only specific air emitted toxic chemicals may explain the difference in the effect size here, relative to the Chinese paper. This effect persists even after controlling for time-varying common shocks, that may affect border-counties and the nature of toxic chemical usage at manufacturing facilities.

Back of the envelop calculation shows that for every $\$0.89c$ increase in wages per hour, air emissions intensity increases by $5.52 lbs$. Furthermore, the reported effect is predominantly driven by both point and fugitive air emissions intensities. These effects are most common in the 2015 and 2017 cohorts, for fugitive air emission intensity, and in the 2014 cohort, for the point air emission intensity. However, I find significant declines in point air emission intensity in the 2015 cohort.

*5.2. Surface Water Discharge Intensity*

Next, I estimate the effect of raising MW on total onsite surface water discharge intensity, using the following model:

$$W_{f,cp,c,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \tag{4}$$

where $W_{f,cp,c,t}$ is the total onsite surface water discharge intensity from a manufacturing industry facility $f$, in cross-border county pairs $cp$, through a toxic chemical $c$, in the year $t$.

Surface water discharge intensity is the total weight of toxic chemical intensity, in the form of contaminants, or wastewater from industrial or commercial facilities, that are released into surface water bodies such as streams. Example of the top five toxic chemical intensity released into surface water bodies, as in Figure 14 of Appendix II, include barium compounds, ammonia, manganese compounds, nickel compounds, and zinc compounds. This discharge can occur through various pathways, including direct discharge through pipes, drains, or outfalls, as well as through runoff from facility surfaces or surrounding areas. Surface water discharge at facilities is regulated by the Clean Water Act of 1972 to protect water quality, safeguard human health, and preserve aquatic ecosystems. Facilities are often required to obtain permits, monitor their discharge, and implement pollution control measures to minimize the impact of their activities on surface water resources.

Table 5: Effect of the MW policy on Onsite Surface Water Discharge Intensity

| Surface water discharge intensity (log) | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $Treated^{e}$ | 0.122* | 0.028 | 0.026 | 0.013 |
| | (0.071) | (0.032) | (0.033) | (0.031) |
| cohort 2014 | 0.032 | -0.037 | -0.028 | -0.054* |
| | (0.035) | (0.024) | (0.025) | (0.030) |
| cohort 2015 | 0.272* | 0.136** | 0.117** | 0.125*** |
| | (0.153) | (0.063) | (0.059) | (0.046) |
| cohort 2017 | 0.316** | 0.069** | 0.073** | 0.096** |
| | (0.131) | (0.032) | (0.033) | (0.041) |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | No | Yes | Yes | Yes |
| toxic chemical × year FEs | No | No | Yes | Yes |
| border-county pair × year FEs | No | No | No | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.082 | 0.297 | 0.585 | 0.592 |
| Baseline Mean | 20.04 | 20.04 | 20.04 | 20.04 |

NOTES: These results are obtained from estimating model 4. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry, and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

The ATT is captured by $\beta$, which is the difference in the average effect of raising the MW floor on total surface water discharge intensity, at manufacturing industry facilities, in treated counties relative to adjacent control counties. The results on total

surface water discharge are reported in Table 5. I find no statistically significant differences in the overall positive effect of raising MW on surface water discharge intensity. However, I find heterogeneous effect across cohorts, after controlling for time-varying common shocks. Whereas raising MW, significantly increases surface water discharge intensity in the 2015 and 2017 cohorts, it declines in the 2014 cohort. The positive effect in the 2015 and 2017 cohorts, results in averages of 2.50*ppts* and 1.92*ppts* of surface water discharge intensity in treated counties, respectively. This heterogeneity is tied to industry composition and regulatory factors.

### *5.3. Land Releases Intensity*

Lastly, I estimate the effect of raising MW on total onsite land releases intensity. The model is given by:

$$L_{f,cp,c,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \tag{5}$$

where $L_{f,cp,c,t}$ is the total onsite land releases intensity from manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical $c$, in the year $t$. Total onsite land releases intensity is the total weight of toxic chemical intensity, that are released to land, for further waste management or disposal. Examples of the top five toxic chemical intensity, according to Figure 15, include barium, and barium compounds, ammonia, chromium and copper.

Table 6: Effect of the MW policy on Onsite Land Releases Intensity

| Land releases intensity (log) | Total | | Components | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | Underground Injection | Landfills | To-Land Treatment | Surface Impoundment |
| $Treated^{e}$ | -0.018 | -0.013 | 0.000 | 0.001 | 0.004 | 0.012* |
| | (0.017) | (0.016) | (0.000) | (0.003) | (0.011) | (0.006) |
| cohort 2014 | -0.003 | -0.009 | 0.000 | 0.007* | 0.003 | 0.014* |
| | (0.021) | (0.024) | (0.001) | (0.004) | (0.018) | (0.008) |
| cohort 2015 | -0.044 | -0.020 | -0.000 | -0.010 | 0.007 | 0.008* |
| | (0.033) | (0.021) | (0.001) | (0.008) | (0.010) | (0.005) |
| cohort 2017 | 0.061** | 0.078** | 0.001 | 0.006 | 0.024 | 0.011* |
| | (0.031) | (0.034) | (0.001) | (0.006) | (0.019) | (0.005) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | No | Yes | Yes | Yes | Yes | Yes |
| border-county pair × year FEs | No | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.500 | 0.506 | 0.387 | 0.468 | 0.331 | 0.158 |
| Baseline Mean | 7.93 | 7.93 | 4.80 | 1.43 | 0.66 | 0.03 |

NOTES: These results are obtained from estimating model 5. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

The ATT is captured by $\beta$, which is the difference in the average effect of raising the MW floor on total onsite land releases intensity, at manufacturing industry facilities in treated counties relative to adjacent control counties. The results are reported in Table 6. Except for the total surface impoundment intensity, I find no statistically or economically significant effect on the intensities of total land releases, underground injection, landfills and to-land treatment (releases used for land fertilization). Although I find an increase in total land releases intensity, and landfill intensity, in the 2017 and 2014 cohorts only, by 7.8*ppts* and 0.7*ppts*, respectively.

A surface impoundment is a type of containment structure, used for the storage and management of liquid wastes, such as

industrial wastewater, hazardous chemicals, or contaminated water. It consists of an excavated depression or basin lined with impermeable materials, such as clay or synthetic liners to prevent the leakage of liquids into the surrounding soil and groundwater. The results show that a higher MW floor increases total surface impoundment intensity by $1.2ppts$, and across all cohorts.

## 6. Robustness Exercises

I conduct three robustness exercises to raise the credibility in the above results. They include determining if the results are driven by major polluting industries, a placebo exercise, and sensitivity exercise by alternatively clustering the standard errors.

### *6.1. Major Polluting Industries*

There are manufacturing industries that release and emit the most toxic chemicals than any other. This subsection investigates if the documented effects are ubiquitous, or entirely driven by such highest emitting manufacturing industries. They include the chemical, food, and leather and allied products manufacturing industries (see their distributions in Figures 22, 23, 24 and 25 of Appendix III).

To investigate the differential effect of higher MW on total onsite toxic release intensity, for the highest emitting manufacturing industries (HEIs), I estimate the following model:

$$\begin{aligned} P^{heis}_{f,cp,c,t} = \beta(Treated^{e} \cdot B)_{f,s,t} + \psi(Treated^{e})_{s,t} + \vartheta(Treated \cdot B)_{f,s,t} + \mu(Post \cdot B)_{f,s,t} \\ + \tau Treated_{s,t} + \rho B_{f,s,t} + \alpha Post_{t} + \sigma X_{v,c,t-1} + \omega F_{f,t} + \lambda_{t} + \gamma_{f} + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \end{aligned} \tag{6}$$

where $P^{heis}_{f,cp,c,t}$, is the vector of total onsite release intensity (air, water and land) of toxic chemicals at a manufacturing industry facility $f$, in a cross-border county pair $cp$, through a toxic chemical $c$, in the year $t$. $Treated_{s,t}$, is a dummy that is equal to 1 for the treated states, and 0 the control states. $Post_{t}$, is a dummy that is equal to 1 if the year $t$ is a post-treatment year, and 0 otherwise. And $B_{f,s,t}$, is a dummy that is unity for the set of HEIs (chemical, food, and leather and allied products manufacturing industries) $f$, in state $s$, in the year $t$, and 0 for low and other lowest emitting manufacturing industries (LEIs).

Table 7: Onsite Releases Intensity given Highest Emitting Manufacturing Industries

| Onsite releases intensity (log) | total | air emissions air | water discharge | land releases |
|---|---|---|---|---|
| $Treated^e \cdot B$ | 0.255*** | 0.162*** | 0.045 | 0.033 |
| | (0.079) | (0.055) | (0.049) | (0.026) |
| $Treated^e$ | 0.052 | 0.038 | 0.018 | 0.003 |
| | (0.039) | (0.035) | (0.020) | (0.011) |
| cohort 2014 $\cdot B$ | 0.252*** | 0.229** | -0.077 | 0.037 |
| | (0.092) | (0.094) | (0.054) | (0.041) |
| cohort 2015 $\cdot B$ | 0.259*** | 0.100* | 0.158*** | 0.030 |
| | (0.089) | (0.059) | (0.054) | (0.044) |
| cohort 2017 $\cdot B$ | -0.181 | -0.115 | -0.123 | 0.017 |
| | (0.172) | (0.171) | (0.093) | (0.026) |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes |
| toxic chemical $\times$ year FEs | Yes | Yes | Yes | Yes |
| border-county pair $\times$ year FEs | Yes | Yes | Yes | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.727 | 0.745 | 0.593 | 0.508 |

NOTES: These results are obtained from estimating equation 6. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

The parameter of interest here is the triple-differences parameter $\beta$, which measures the differential impact on total onsite toxic release intensities, due to a higher MW policy, for HEIs. $\psi$, measures the relative change for LEIs. And $\beta+\psi$, measures the total relative change for the HEIs.

The results are presented in Table 7. I find that the increasing total onsite toxic release intensities, are predominantly observed in highest-emitting manufacturing industries, rising by a much sizable magnitude, of $26 ppts$. This reflects a quantifiable increase of $22.88 lbs$, an increase from $9.68 lbs$ in Section 5. This effect is most notable in the 2014 and 2015 cohorts, and is primarily driven by the intensities of total air emissions, and surface water discharge, in the 2015 cohort. I find limited evidence of an increase in land releases intensity. Likewise, I find limited evidence of a significant increase in total onsite toxic release intensity, among LEIs.

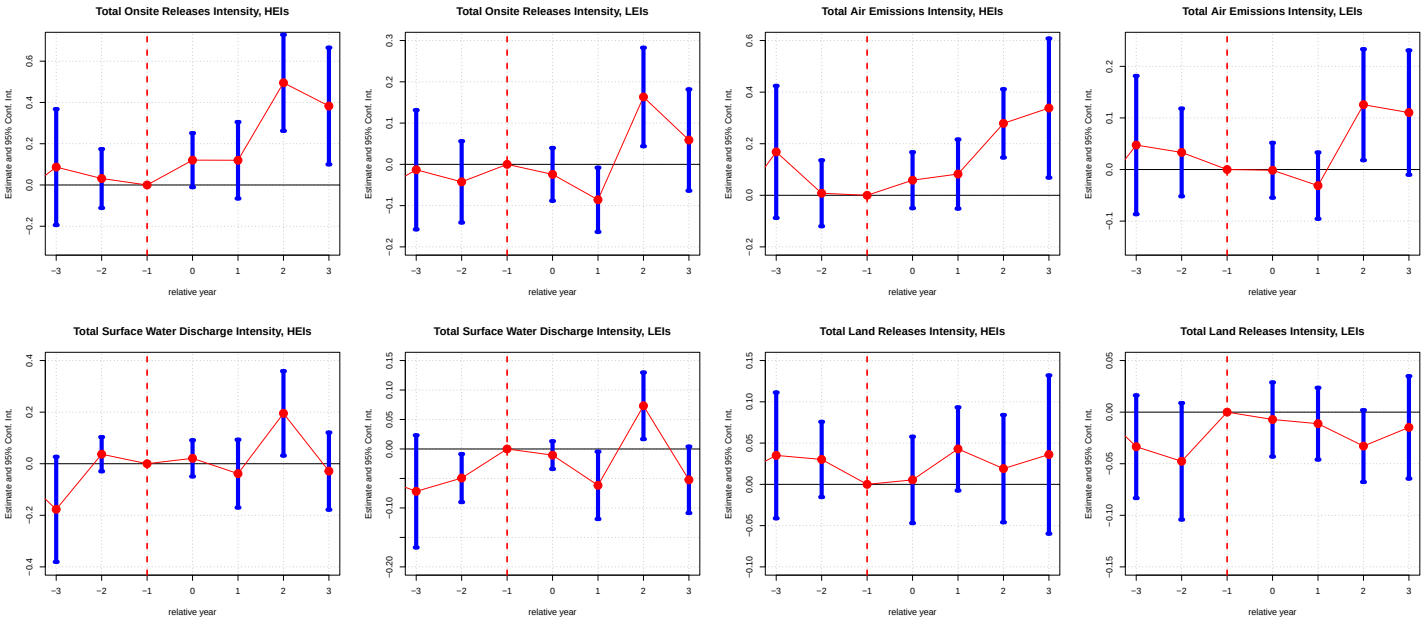



Figure 6: Triple-Differences: Onsite Total Releases Intensity given Highest Emitting Manufacturing Industries

NOTES: The event study model of equation 6 is $P^{heis}_{f,cp,c,t} = \sum_{e=-3,e\neq-1}^{3} \beta(Treated^{e} \cdot D)_{f,s,t} + \psi(Treated^{e})_{s,t} + \vartheta(Treated \cdot D)_{f,s,t} + \mu(Post \cdot D)_{f,s,t} + \tau Treated_{s,t} + \rho D_{f,s,t} + \alpha Post_{t} + \sigma X_{v,c,t-1} + \omega F_{f,t} + \lambda_{t} + \gamma_{f} + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}$. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry, and state levels. HEIs mean highest emitting industries.

Figure 6, illustrates the dynamic effects of higher MW policies. The results indicate that the positive effects on onsite toxic release intensity are present in both the HEIs and LEIs. For the HEIs, the increase is instantaneous and persists for up to three years later, reaching a staggering 45*ppts* in the second year, before receding to 40*ppts* in the third year. For the LEIs, the effect declines in the first year, but rises in the second year, with a positive difference of 6*ppts* in the third year. These effects are especially evident in total air emissions, and surface water discharge intensities, emerging in the second year of the post-treatment period. The impact on land release intensity is generally limited.

### *6.2. Placebo Exercise*

To increase the credibility in the reported results, I model the placebo effect of raising the MW on total release intensity, from catastrophic events. Such events include accidental chemical spills, fire, explosions and natural disasters at manufacturing facilities. These catastrophic events are expected to be uncorrelated with the MW policy. Hence, I do not expect to see any statistically significant effect on such onsite toxic release intensity. I estimate the following model:

$$P^{catastrophic}_{f,cp,c,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_{t} + \gamma_{f} + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \tag{7}$$

where $P_{f,cp,c,t}$ is the total onsite toxic release intensity from catastrophic events, at manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical use $c$, in the year $t$.

The ATT measures the difference in the average effect of raising the MW, on total onsite releases intensity from catastrophic events at manufacturing industry facilities, in treated counties relative to adjacent control counties. The results are presented in Table 17 of Appendix II. Indeed, the result is consistent with the null hypothesis. This effect remains unchanged after controlling for common time-varying shocks affecting the nature of toxic chemical usage, and border-counties in columns 3

and 4, respectively. Additionally, Figure 20 of the same Appendix, shows the dynamic placebo effect, revealing a null response in total onsite toxic release intensity from catastrophic events, and no evidence of significant pre-trends.

### *6.3. Alternative Clustering of the SEs*

The results in Tables 18, 19, 20, and 21 of Appendix II remain insensitive to alternative clustering of the standard errors.

I have shown that a higher MW policy caused an increase in total onsite toxic release intensity, across all cohorts, and concentrated in the chemical, food, leather and allied products manufacturing industries, in the 2014 and 2015 cohorts. This effect is driven by corresponding increases in the intensities of total air emissions (both from point and fugitive sources), and surface water discharge, regardless of the increases in land releases intensity, particularly surface impoundment intensity.

Next, I characterize the the heterogeneous treatment effects of the above results.

## 7. Heterogeneous Treatment Effects

To address the second question, on whether the increased total onsite toxic release intensity is heterogeneous, I estimate the following model:

$$\begin{aligned} P_{f,cp,c,t} = {} & \beta(Treated^{e} \cdot D^{h})_{f,s,t} + \psi(Treated^{e})_{s,t} + \vartheta(Treated \cdot D^{h})_{f,s,t} + \mu(Post \cdot D^{h})_{f,s,t} \\ & + \tau Treated_{s,t} + \rho D^{h}_{f,s,t} + \alpha Post_{t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_{t} + \gamma_{f} + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}, \end{aligned} \tag{8}$$

where $P_{f,cp,c,t}$, is the total onsite toxic release intensity, at manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical use $c$, in the year $t$. $Post_t$, is a dummy that is equal to 1 if the year $t$ is a post-treatment year, and 0 otherwise. And $D^{h}_{f,s,t} \in \{1, 0\}$, is a vector of dummies of heterogeneous dimensions, such as manufacturing industry's profitability and type of production technology, industry concentration, type of chemicals including carcinogenic chemicals, Clean Air Act (CAA) chemicals and Hazardous Air Pollutants (HAP), and persistent bio-accumulative toxic (PBT) chemicals. [12] Other variables are as defined in Section 5.

The parameter of interest here is the triple-differences parameter $\beta$, which measures the differential ATTs of higher MW on total onsite toxic release intensities, at manufacturing facilities in treated counties relative to adjacent control counties, conditioned on the specific heterogeneous dimension, when $D^{h}_{f,s,t} = 1$. $\psi$ captures the relative differential impact, when $D^{h}_{f,s,t} = 0$. $\beta + \psi$ captures the total relative change, when $D^{h}_{f,s,t} = 1$. To have a causal interpretation, the weaker parallel trends assumption is only required to hold for one of the groups in triple differences (Olden and Møen, 2022). The results are presented in Table 22 and Figure 27 of Appendix III. [13]

[12] CAA chemicals are toxic chemicals heavily regulated under the CAA of 1970. The CAA is a comprehensive federal law enacted by the United States Congress to address air pollution control and improve air quality standards across the nation. The primary goals of the CAA are to protect public health and the environment by regulating the emission of harmful air pollutants. HAPs, also known as air toxics, are pollutants that are known or suspected to cause serious health and environmental effects. These pollutants are regulated under the CAA Amendments of 1990. Additionally, PBTs are a group of chemicals characterized by their persistence in the environment, ability to accumulate in living organisms, and toxicity. These chemicals pose significant risks to human health and the environment due to their long-term effects and potential for biomagnification in food chains.

[13] In theory, companies operating in highly concentrated industries (HCIs), which face less competition, benefit from economies of scale and maintain dominant market positions (Baumol et al., 1982). These firms can absorb exogenous cost shocks due to their large production scales. Moreover, they can transfer the increased labour costs to consumers, through higher sales prices or to suppliers by negotiating lower purchase prices. Consequently, Zhang et al. (2023) argued that HCI industries will exhibit a smaller increase in total onsite toxic release intensity in response to MW hikes. I test whether high concentration (less competitiveness) implies smaller increases in total releases intensities in response to MW increases, when $D^{h}_{f,s,t} = 0$. To gauge market concentration, I employ the Herfindahl-Hirschman Index (HHI) (Zhang et al., 2023; Weinstock, 1982). This index is derived each year, by summing the squared market shares of all firms within a six-digit NAICS industry codes. Utilizing revenue data to compute HHI, I then average these values over the entire sample period, and classify industries based on the median HHI value. A lower Herfindahl-Hirschman Index (HHI) indicates that the industry is less concentrated, and exhibits greater competitiveness $D^{h}_{f,s,t} = 1$. These are industries below the median HHI value. Those above the median HHI value, are classified as high-concentrated industries and exhibit less competition, when $D^{h}_{f,s,t} = 0$. Column 3 and the Figure, show small and limited evidence on total releases intensity, for high-, and low-competitive industries.

*7.1. Profitability and Production Technology*

Economic theory suggests that financial standings and production technology are crucial, in modeling industrial pollution responses. The dummy of labour-intensive manufacturing industries, is proxied by the first-year pre-treatment ratios, of high-payroll-wages-to-revenue and high-production-workers-wages-to-revenue. Capital-intensive manufacturing industries is proxied by the low ratios. [14]

I construct industry profits based on the difference between industry revenue and total cost (the sum of material cost, production workers wages, and energy cost). Thus, the dummy of high-profit industries is constructed, based on the first-year pre-treatment industry profits above-median quantile. Below-median quantile denotes low-profits.

Therefore, I classify manufacturing industries based on their profit levels and type of production technology, to investigate the differential impacts of the above effects. That is $D^{h}_{f,s,t} \in \{1, 0\}$, a vector of each dummy of high-profit-labour-intensive v. high-profit-capital-intensive, and then low-profit-labour-intensive v. low-profit-capital-intensive, manufacturing facilities $f$ in state $s$, in the year, $t$. It is unity for high-profit-labour-intensive, and 0 for high-profit-capital-intensive manufacturing industries. Also, it is unity for low-profit-labour-intensive and 0 for low-profit-capital-intensive manufacturing industries. Zhang et al. (2023) hypothesised that more financially constrained firms and labour-intensive industries, are more responsive to higher MW relative to capital-intensive industries. Hence, I test whether the effects of raising MW on total onsite toxic release intensities, are dominated in either the high- or low-profit-labour-intensive industries.

For the high-profit-labour-intensive manufacturing industries, I find a negative and insignificant effect, in column 1 of Table 22. This observed decline is largely attributable to the significant reduction in the 2015 cohort. The overall relative change $\beta_{2015} + \psi$, for the 2015 cohort, indicates a substantial decrease of 12.3$ppts$. Figure 27, reveals that this decline is immediate and short-lived, dissipating throughout the post-treatment period. Panel A of Figure 17 of Appendix II, shows that this declining effect is common among these top ten toxic chemical release intensities. They are sodium nitrate, nitrate compounds, chloromethane, styrene, acetaldehyde, hydrochloric acid, tetrachloroethylene, sulfuric acid, cresol, and methanol. In contrast, for the high-profit-capital-intensive manufacturing industries, the results show a significant positive effect of 19.9$ppts$, higher than the baseline estimate of 11$ppts$. Similarly, the Figure also show that this positive effect is instantaneous, peaking in the second year of post-treatment. Example of such toxic chemicals in panel B, include nitrate compounds, sulfuric acid, ammonia, vinyl chloride, chloromethane, sec-butyl alcohol, hydrogen cyanide, vinyl acetate, hydrochloric acid, and propylene. There are no notable pre-trends.

For the low-profit-labour-intensive manufacturing industries, the results in column 2 reveal a decreasing differential effect of 17.9$ppts$, due to a higher MW, especially in the 2015 cohort. This decline is strongest in the first and second year of post-treatment. The overall relative change $\beta + \psi$, is a significant decrease of 25.6$ppts$; and for the 2015 cohort $\beta_{2015} + \psi$, a substantial decrease of 33.9$ppts$. These results contradict the argument by Zhang et al. (2023), on high pollution response for financially constrained and labour-intensive manufacturing industries. As discussed in the online supplementary material, this negative effect is associated with the fact that production output remained unchanged, while labour productivity increased in labour intensive industries of both high and low profitability, following a cost shock. Example of such toxic chemicals in

[14] High, denotes above-the-median quantile, and low, denotes below-the-median quantile.

panel C are similar to that of high-profit-labour-intensive manufacturing industries, weighing above $100lbs$, but also includes ammonia, xylene, formaldehyde, dichloromethane, dimethyl phthalate, nn-dimethylformamide, barium, trichloroethylene, methanol, methyl methacrylate, toluene, ethylbenzene, and methyl isobutyl ketone. I find limited evidence of an increase, in low-profit-capital-intensive industries. As expected, there are no significant pre-trends.

### *7.2. Types of Toxic Chemicals*

Here, I check whether the rise in total onsite toxic release intensity is potentially carcinogenic, or persists in highly regulated toxic chemical domains.

The results in Column 4 of Table 22 and Figure 27, show that the documented positive effect is most common in non-carcinogenic toxic chemicals (when $D^h_{f,s,t} = 0$), emerging in the second year of post-treatment. Panel B of Figure 16, lists the most common examples of these non-carcinogenic releases, over $100lbs$ weight. They include nitrate compounds, ammonia, methanol, hydrochloric acid, certain glycol ethers, hydrogen fluoride, ethylene, sulfuric acid, dimethyl phthalate, and chloromethane. However, I find limited evidence of an increase, in carcinogenic toxic chemicals (when $D^h_{f,s,t} = 1$), throughout the post-treatment periods.

Additionally, column 5 shows that the positive effect, is dominated among commonly regulated toxic chemicals, by the CAA of 1970 and 1990 (common CAA-HAPs, when $D^h_{f,s,t} = 1$), in the 2017 cohort. The overall relative change $\beta_{2017} + \psi$, for the 2017 cohort, indicates a substantial increase of $98.2ppts$. This means that the increase in total onsite toxic release intensity, is dominated in manufacturing industries located in the state of Maine. Panel B of Figure 18, plots the list of common CAA-HAPs toxic chemicals, in the top ten total release intensity in Maine. They include, methanol, hydrochloric acid, manganese compounds, acetaldehyde, phenol, methyl methacrylate, and formaldehyde, that are above $100lbs$ weight. Panel A, shows additional toxic chemical releases, such as certain glycol ethers, hydrogen flouride, styrene, dimethyle phthalate, vinyl chloride, chloromethane, and acrolein. I find an insignificant effect for toxic chemicals not common in both acts (uncommon CAA-HAPs, when $D^h_{f,s,t} = 0$). However, a positive effect on these toxic chemicals emerged in the second year of post-treatment. Some of them are nitrate compounds, ammonia, ethylene, sulfuric acid, hydrogen cyanide, sodium nitrate, n-butyl alcohol, barium, and barium compounds. There are no notable pre-trends. The health implications of such emissions are well documented in the literature, concluding that cancers in humans and aquatic lives, reductions in infant birth weights, rising bronchitis and respiratory illnesses in toddlers, are caused by rising air and water pollution, respectively (Turner et al., 2020, 2017; Baines et al., 2021; Coneus and Spiess, 2012).

Finally, column 6 shows that the increasing total onsite toxic release intensity is dominated in non-PBT chemicals. Panel B of Figure 19, plots the list of the most common non-PBT chemical release intensities. They are essentially, a combined list of the most common and uncommon CAA and HAPs, and carcinogenic and non-carcinogenic chemical releases. Furthermore, I find substantial decline in PBT chemicals (when $D^h_{f,s,t} = 1$), in the 2017 cohort. Panel A, shows that the most common of these PBT chemicals include, lead compounds, benzoperylene, polycyclic aromatic compounds, tetrabromobisphenol, lead, mercury and mercury compounds. This decline is instantaneous, peaking in the second year of post-treatment, at $26ppts$. There are no notable pre-trends.

## 8. Mechanism Analyses

This section addresses the third question. In a two-step process involving identifying the mechanisms and moderation effects, I investigate the transmission mechanisms of the increasing onsite total toxic release intensity, due to exogenous cost shocks from higher MW, through onsite source reduction activities. Source reduction activities refers to any practice that minimizes or eliminates the generation of toxic wastes or pollutants, in production processes, before they enter any waste stream or get released into the environment. This is also referred to as Pollution Prevention (P2). These activities aim to minimize or eliminate the creation of toxic waste materials, or the use of hazardous substances in manufacturing processes. Therefore, I estimate the following model.

$$M_{f,cp,c,t} = \beta Treated^{e}_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t} \tag{9}$$

Where $M_{f,cp,c,t}$, is the vector of onsite source reduction activities including effective operating practices and training, improved material handling, improved procedures for loading, unloading, and transfer of toxic chemicals at manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical use $c$, in the year $t$. Other right-hand-side variables are as defined in Section 5. The ATT is captured by $\beta$, which is the difference in the average effect of raising the MW floor on the mechanisms at manufacturing industry facilities in treated counties relative to adjacent control counties. The results are reported in Table 8.

Table 8: Onsite Transmission Mechanisms

| mechanisms | sra | improved material handling | improved procedures for loading | operating practices and training |
|---|---|---|---|---|
| $Treated^{e}$ | -0.008*** | -0.004*** | -0.002* | -0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | Yes | Yes | Yes | Yes |
| border-county × year FEs | Yes | Yes | Yes | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.476 | 0.409 | 0.149 | 0.165 |

NOTES: These results are obtained from estimating model 9. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively. SRA denotes source reduction activities.

The mechanism results show that, given higher labour cost induced by the MW policy, there are significant declines in investments into source reduction activities, at onsite manufacturing facilities, in treated counties relative to the controls. Specifically, these declines are in effective operating practices and training, improved material handling, and improved procedures for loading, unloading, and transfer of toxic chemicals, as a tradeoff for the higher labour cost.

Manufacturing industry facilities implement effective operating practices, including optimized raw material handling through advanced techniques, enhanced operating and process control practices, and improved raw material input to reduce scrap and increase yield. The facilities track chemical consumption daily, investigates deviations, and promptly manages spills to minimize waste and emissions. Efficient management practices, training, and acquiring more efficient production equipment such as flatline spray booths further enhance waste elimination efforts.

The facility minimizes raw material and finished product losses through advanced material handling techniques and the installation of closed hose systems and new mechanical seals to reduce leakage during transfers and packaging. Automated material handling systems prioritize safety, reducing the chance of spills. Vendor collaboration and improved handling techniques help to reduce scrap. Improved waste solder dross handling has increased lead recovery, enhancing waste minimization efforts.

The facility has implemented improved loading and unloading procedures to ensure correct product-to-tank transfers and improved security. The use of a sealed/clamped system for methanol loading minimizes fugitive losses. Streamlined weighing systems resolve yield number conflicts, and facilities install new pumps and hoses to boost operational efficiency. Emissions during ethanol production, both hexane and methanol, are strictly monitored and controlled through improved handling and storage techniques.

Table 9: Onsite Transmission Mechanisms: Moderation Effects

| Total Release Intensity (log) | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $Treated^e \cdot M$ | -0.846*** | -0.439*** | -1.650*** | -1.330*** |
| | (0.200) | (0.142) | (0.193) | (0.282) |
| $Treated^e$ | 0.130*** | 0.129*** | 0.130*** | 0.131*** |
| | (0.049) | (0.049) | (0.049) | (0.049) |
| source reduction activities | ✓ | | | |
| improved material handling | | ✓ | | |
| improved procedures for loading | | | ✓ | |
| operating practices and training | | | | ✓ |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | Yes | Yes | Yes | Yes |
| border-county × year FEs | Yes | Yes | Yes | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.726 | 0.726 | 0.726 | 0.726 |

NOTES: These results are obtained from estimating this model: $P_{f,cp,c,t} = \beta(Treated^e \cdot M)_{f,s,t} + \psi(Treated^e)_{s,t} + \vartheta(Treated \cdot M)_{f,s,t} + \mu(Post \cdot M)_{f,s,t} + \tau Treated_{s,t} + \rho M_{f,s,t} + \alpha Post_t + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}$, where $P_{f,cp,c,t}$, is the total onsite toxic release intensity, at manufacturing industry facility $f$, in cross-border county pairs $cp$, through toxic chemical use $c$, in the year $t$. $Post_t$, is a dummy that is equal to 1 if the year $t$, is a post-treatment year, and 0, otherwise. And $M^h_{f,s,t} \in \{1, 0\}$, is a vector of dummies of source reduction activities, such as effective operating practices and training, improved material handling, improved procedures for loading, unloading, and transfer of toxic chemicals at manufacturing facilities. Other variables are as defined in Section 5. The parameter of interest here is the triple-differences parameter $\beta$, which measures the differential moderation ATTs on onsite total toxic release intensities, at manufacturing facilities in treated counties relative to adjacent control counties, conditioned on the presence of source reduction activities, when $M_{f,s,t} = 1$. $\psi$ captures the relative differential impact, when $M_{f,s,t} = 0$, suggesting the absence of source reduction activities, or no moderation effect. $\beta + \psi$ captures the total relative change, moderated when $M_{f,s,t} = 1$. Furthermore, rows $5 - 8$ are the moderating variables in the $M$ vector. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

However, the increased labour costs induced by the higher MW reduce investments in the above source reduction practices, leading to higher onsite total toxic release intensity. These mechanisms are further detailed in the moderation effects in Table 9. While the onsite total toxic release intensity generally increases in treated counties relative to control counties, it significantly reduces when moderated by source reduction activities, such as effective operating practices and training,

improved material handling, and enhanced procedures for loading, unloading, and transferring toxic chemicals. Thus, these source reduction activities mitigate the overall positive impact on onsite toxic release intensity. These effects align with the crowding-out effect hypothesis, highlighting the importance of combining effective operating practices, material handling improvements, and transfer procedures to combat pollution in states with higher labour costs due to the MW.

## 9. Concluding Remarks

This paper utilizes precise administrative toxic release inventory, and manufacturing industry payroll data, to provide compelling empirical evidence on the environmental consequences of raising the statutory minimum wage, in the United States. Specifically, I investigate the causal impact of minimum wage increases on onsite total toxic release intensity, including the intensities from air emissions, surface water discharges, and land releases, at manufacturing facilities in cross-border counties. Employing a staggered difference-in-differences (DiD) design with a multi-way clustering of standard errors, my analysis reveals several important findings.

The preliminary findings provide causal evidence of increased cost burdens in both low-skilled, and spillovers to high-skilled workers, as well as in the cost of production materials, due to a higher MW floor. This is followed by rising outputs, labour productivity, and profits. Although overall effects on employment and production workers' hours are null, cohort-specific effects are more nuanced. Disemployment is more pronounced among low-skilled workers, while positive employment effects dominate in high-skilled workers. The disemployment effect for low-skilled workers is primarily driven by their reluctance to commute to distant higher MW counties/states, whereas the increasing demand for high-skilled workers is caused by the MW policy and independent of cross-county/state worker mobility. However, there is notable decline in material cost, and profits in the 2017 cohort from a corresponding disemployment effect, and output decline. These preliminary findings have significant implications for the environmental consequences of the higher MW policy.

First, the results indicate a statistically significant increase in total onsite toxic release intensity, following an exogenous rise in minimum wages. The estimated ATT shows that for every $\$0.89c$ increase in hourly wages, there is an additional $9.68lbs$ of toxic releases per \$100 million units of manufacturing output. This effect persists across all cohorts, and is robust to controlling for facility-level characteristics, toxic chemical attributes, and common time-varying shocks. Narrowing in on the highest emitting industries—chemical, food, leather and allied products manufacturing—I find that the effect further increased to $22.88lbs$. The top twenty emitted toxic chemical intensities, include nitrate compounds, ammonia, acetaldehyde, formaldehyde, methanol, hydrochloric acid, certain glycol ethers, hydrogen fluoride, ethylene, sulfuric acid, styrene, dimethyl phthalate, vinyl chloride, chloromethane, hydrogen cyanide, sodium nitrite, acrolein, n-butyl alcohol, barium, and barium compounds. This suggests that wage hikes may inadvertently intensify pollution, by increasing production costs and altering operational behaviour at manufacturing plants.

Second, tracing the source of this increase, I find that higher minimum wages lead to a substantial rise in air emissions intensity, driven by both point and fugitive air emissions. While the magnitude of the effect is smaller than that reported in similar studies on Chinese manufacturing industries, the results align with broader environmental economics literature linking economic growth with pollutant emissions. Notably, the effect persists across different cohorts and is most pronounced in

fugitive emissions during the post-2015 period.

Third, the analysis on surface water discharge intensity yields mixed results. While the overall effect is positive but statistically insignificant, I uncover significant heterogeneity across cohorts. Specifically, surface water discharge intensity rises significantly in the 2015 and 2017 cohorts, but declines in the 2014 cohort. This nuanced finding underscores the need for further investigation into the role of cohort-specific factors, such as industry composition, regulatory compliance, and technological adaptation, in shaping environmental outcomes.

The heterogeneous characterizations reveal that, the increasing toxic release intensities persists even in highly regulated toxic chemical domains, and are dominated among non-PBT chemicals, which are a combined list of toxic chemicals and HAPs regulated by the Clean Air Act of 1970 and 1990, which are potentially carcinogenic to all flora and fauna. These positive effects are also most common among high-profit-capital-intensive manufacturing industries, whereas it declines for low- and high-profit-labour-intensive industries.

The mechanism analysis indicates that higher labour costs, driven by minimum wage increases, tend to elevate total toxic release intensity at manufacturing facilities, transmitted by disinvestments in onsite source reduction activities. This effect is mitigated by the implementation of source reduction activities, such as operating practices and training, improved material handling, and enhanced loading and transfer procedures, which effectively reduce overall pollution intensity. The analysis supports the crowding-out effect hypothesis, emphasizing the crucial role of these operational practices in counterbalancing the adverse environmental impacts of increased labour costs. Ultimately, integrating robust pollution control measures in these activities is essential for maintaining environmental performance despite higher labour costs.

These findings contribute to the growing literature on the unintended consequences of labour market policies. They suggest that while minimum wage policies can improve workers' welfare by raising earnings, they may also generate negative externalities in the form of increased pollution. Policymakers should be mindful of these trade-offs, and consider complementary environmental regulations or incentives on the aforementioned on source reduction activities, to mitigate potential adverse environmental impacts.

Future research could explore the long-term dynamics of these effects, including potential non-linearity and threshold effects. Additionally, examining how firms' investment in pollution control technologies responds to minimum wage hikes could provide deeper insights into the mechanisms driving these outcomes. By linking labour economics with environmental economics, this paper offers a holistic perspective on the broader implications of labour market interventions, paving the way for more integrated and sustainable policy design.

# Appendices

## I. State Minimum Wage and Balance Tests

Table 10: Minimum Wage Changes in US States from 2011 – 2017

| states | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | start MW | end MW |
|---|---|---|---|---|---|---|---|---|---|
| Alaska | 0 | 0 | 0 | 0 | 1 | 1 | 0.05 | 7.75 | 9.8 |
| Arkansas | 0 | 0 | 0 | 0 | 1.25 | 0.5 | 0.5 | 6.25 | 8.5 |
| Arizona | 0.1 | 0.3 | 0.15 | 0.1 | 0.15 | 0 | 1.95 | 7.35 | 10 |
| California | 0 | 0 | 0 | 1 | 0 | 1 | 0.5 | 8 | 10.5 |
| Colorado | 0.12 | 0.28 | 0.14 | 0.22 | 0.23 | 0.08 | 0.99 | 7.36 | 9.3 |
| Connecticut | 0 | 0 | 0 | 0.45 | 0.45 | 0.45 | 0.5 | 8.25 | 10.1 |
| Delaware | 0 | 0 | 0 | 0.5 | 0.5 | 0 | 0 | 7.25 | 8.25 |
| Florida | 0 | 0.42 | 0.12 | 0.14 | 0.12 | 0 | 0.05 | 7.21 | 8.1 |
| Georgia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5.15 | 5.15 |
| Hawaii | 0 | 0 | 0 | 0 | 0.5 | 0.75 | 0.75 | 7.25 | 9.25 |
| Iowa | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Idaho | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Illinois | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8.25 | 8.25 |
| Indiana | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Kansas | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Kentucky | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Massachusetts | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 8 | 11 |
| Maryland | 0 | 0 | 0 | 0 | 1 | 0.5 | 0.5 | 7.25 | 9.25 |
| Maine | 0 | 0 | 0 | 0 | 0 | 0 | 1.5 | 7.5 | 9 |
| Michigan | 0 | 0 | 0 | 0.75 | 0 | 0.35 | 0.4 | 7.4 | 8.9 |
| Minnesota | 0 | 0 | -0.01 | 1.85 | 1 | 0.5 | 0 | 6.16 | 9.5 |
| Missouri | 0 | 0 | 0.1 | 0.15 | 0.15 | 0 | 0.05 | 7.25 | 7.7 |
| Montana | 0.1 | 0.3 | 0.15 | 0.1 | 0.15 | 0 | 0.1 | 7.35 | 8.15 |
| North Carolina | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| North Dakota | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Nebraska | 0 | 0 | 0 | 0 | 0.75 | 1 | 0 | 7.25 | 9 |
| New Hampshire | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| New Jersey | 0 | 0 | 0 | 1 | 0.13 | 0 | 0.06 | 7.25 | 8.44 |
| New Mexico | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.5 | 7.5 |
| Nevada | 0.7 | 0 | 0 | 0 | 0 | 0 | 0 | 8.25 | 8.25 |
| New York | 0 | 0 | 0 | 0.75 | 0.75 | 0.25 | 0.7 | 7.25 | 9.7 |
| Ohio | 0.1 | 0.3 | 0.15 | 0.1 | 0.15 | 0 | 0.05 | 7.4 | 8.1 |
| Oklahoma | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Oregon | 0.1 | 0.3 | 0.15 | 0.15 | 0.15 | 0.5 | 0.5 | 8.5 | 10.25 |
| Pennsylvania | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Rhode Island | 0 | 0 | 0.35 | 0.25 | 1 | 0.6 | 0 | 7.4 | 9.6 |
| South Dakota | 0 | 0 | 0 | 0 | 1.25 | 0.05 | 0.1 | 7.25 | 8.65 |
| Texas | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Utah | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Virgina | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| Vermont | 0.09 | 0.31 | 0.14 | 0.13 | 0.42 | 0.45 | 0.4 | 8.15 | 10 |
| Washington | 0.12 | 0.37 | 0.15 | 0.13 | 0.15 | 0 | 1.53 | 8.67 | 11 |
| Wisconsin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.25 | 7.25 |
| West Virginia | 0 | 0 | 0 | 0 | 0.75 | 0.75 | 0 | 7.25 | 8.75 |
| Wyoming | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5.15 | 5.15 |

Table 11: Balance Test: Treated v. Control Border Counties

| | Treated | | Control | | Differences and p-value | |
|---|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Mean Differences | Prob. Value |
| GDP per capita (1000's) | 49.71 | 10.80 | 48.65 | 11.13 | 1.06 | 0.81 |
| industry employment (1000's) | 46.10 | 36.78 | 44.69 | 43.68 | 1.41 | 0.93 |
| annual average establishments | 2.72 | 5.62 | 6.19 | 13.57 | -3.47 | 0.41 |
| city wide consumer price index ($) | 233 | 6.97 | 236 | 6.17 | -2.97 | 0.25 |
| chemical ancillary use (onsite) | 0.48 | 0.50 | 0.18 | 0.39 | 0.30 | 0.10 |
| chemical formulation component (onsite) | 0.46 | 0.50 | 0.28 | 0.45 | 0.18 | 0.35 |
| chemical manufacturing aid (onsite) | 0.11 | 0.31 | 0.10 | 0.31 | 0.01 | 0.94 |
| max number of chemicals at facility (onsite) | 3.81 | 1.51 | 3.91 | 1.41 | -0.10 | 0.87 |
| entire facility (onsite) | 0.99 | 0.12 | 1.00 | 0.02 | -0.01 | 0.78 |
| private facility (onsite) | 1.00 | 0.00 | 1.00 | 0.01 | 0.00 | 1.00 |
| imported chemicals at facility (onsite) | 0.10 | 0.31 | 0.05 | 0.23 | 0.05 | 0.65 |
| produced chemicals at facility (onsite) | 0.36 | 0.48 | 0.20 | 0.40 | 0.16 | 0.38 |
| production ratio or activity index (onsite) | 2.84 | 383.34 | 1.25 | 16.22 | 1.59 | 0.99 |

NOTES: The table compare county-level pre-treatment covariates of the treated relative to the control states. The sample is restricted to border counties in treated and control states (See Table 1).

Table 12: Balance Test: Treated v. Control Border States

| | Treated | | Control | | Differences and p-value | |
|---|---|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD | Mean Differences | Prob. Value |
| GDP per capita (1000's) | 47.28 | 13.13 | 49.34 | 11.45 | -2.06 | 0.68 |
| industry employment (1000's) | 49.64 | 51.92 | 46.86 | 49.14 | 2.78 | 0.89 |
| annual average establishments | 3.89 | 6.72 | 10.34 | 25.18 | -6.45 | 0.39 |
| city wide consumer price index ($) | 235 | 6.22 | 236 | 6.19 | -0.11 | 0.96 |
| chemical ancillary use (onsite) | 0.23 | 0.42 | 0.17 | 0.38 | 0.06 | 0.71 |
| chemical formulation component (onsite) | 0.25 | 0.43 | 0.25 | 0.43 | 0.00 | 1.00 |
| chemical manufacturing aid (onsite) | 0.12 | 0.32 | 0.10 | 0.30 | 0.02 | 0.87 |
| max number of chemicals at facility (onsite) | 3.66 | 1.75 | 3.78 | 1.54 | -0.12 | 0.86 |
| entire facility (onsite) | 0.99 | 0.11 | 1.00 | 0.04 | -0.01 | 0.77 |
| private facility (onsite) | 1.00 | 0.00 | 1.00 | 0.02 | 0.00 | 1.00 |
| imported chemicals at facility (onsite) | 0.08 | 0.27 | 0.07 | 0.25 | 0.01 | 0.92 |
| produced chemicals at facility (onsite) | 0.32 | 0.47 | 0.25 | 0.43 | 0.07 | 0.70 |
| production ratio or activity index (onsite) | 9.88 | 932.41 | 1.48 | 25.25 | 8.40 | 0.98 |

NOTES: The table compare county-level pre-treatment covariates of the treated relative to the control states. The sample is restricted to border counties in treated and control states (See Table 1).

Table 13: Summary Statistics (Onsite)

| Variable | Obs | Mean | StdDev | Min | Max |
|---|---|---|---|---|---|
| GDP per capita ($1000) | 1893689 | 48.88 | 11.07 | 19.60 | 163.74 |
| industry employment (1000's) | 1893689 | 44.99 | 42.29 | 2.90 | 365.80 |
| annual average establishments | 1893689 | 5.44 | 12.38 | 0.00 | 330.00 |
| population (county) (1000's) | 1893689 | 693432.18 | 1247538.81 | 1466.00 | 5194675.00 |
| city region average consumer price index ($) | 1893689 | 235.46 | 6.47 | 224.94 | 245.12 |
| federal facility | 1893689 | 0.00 | 0.01 | 0.00 | 1.00 |
| chemical ancillary use | 1893689 | 0.25 | 0.43 | 0.00 | 1.00 |
| chemical formulation component | 1893689 | 0.32 | 0.47 | 0.00 | 1.00 |
| chemical manufacturing aid | 1893689 | 0.11 | 0.31 | 0.00 | 1.00 |
| max number of chemicals at facility | 1893689 | 3.89 | 1.43 | 1.0 | 19.00 |
| imported chemicals at facility | 1893689 | 0.07 | 0.25 | 0.0 | 1.00 |
| produced chemicals at facility | 1893689 | 0.24 | 0.42 | 0.0 | 1.00 |
| production ratio or activity index | 1893689 | 1.59 | 178.58 | 0.0 | 117229.00 |
| total releases intensity (lbs) | 1893689 | 87.99 | 1065.44 | 0.00 | 122005.98 |
| total air emissions intensity (lbs) | 1893689 | 60.02 | 616.84 | 0.00 | 40743.89 |
| total fugitive air emissions intensity (lbs) | 1893689 | 10.95 | 163.84 | 0.00 | 21484.45 |
| total point air emissions intensity (lbs) | 1893689 | 49.07 | 537.76 | 0.00 | 31559.41 |
| total land releases intensity (lbs) | 1893689 | 7.93 | 701.61 | 0.00 | 122005.98 |
| total underground injection intensity (lbs) | 1893689 | 4.80 | 697.74 | 0.00 | 122005.98 |
| total landfills intensity (lbs) | 1893689 | 1.43 | 53.40 | 0.00 | 6892.31 |
| total releases to-land treatment intensity (lbs) | 1893689 | 0.66 | 34.58 | 0.00 | 6006.01 |
| total surface impoundment intensity (lbs) | 1893689 | 0.03 | 2.40 | 0.00 | 929.15 |
| total land releases intensity, others (lbs) | 1893689 | 1.01 | 30.47 | 0.00 | 2299.05 |
| total surface water discharge intensity (lbs) | 1893689 | 20.04 | 475.39 | 0.00 | 41422.43 |
| total number of receiving streams, onsite (lbs) | 1893689 | 0.39 | 0.50 | 0.00 | 4.00 |
| total release intensity, from catastrophic events (lbs) | 1893689 | 4.36 | 249.63 | 0.00 | 42103.29 |
| total industry payroll ($1$m$) | 1893689 | 2962.68 | 2630.57 | 127.00 | 16647.90 |
| production workers (1000's) | 1893689 | 31.42 | 31.71 | 1.40 | 280.60 |
| production hours (1m) | 1893689 | 64.82 | 63.90 | 3.10 | 561.50 |
| production workers' wages per hour | 1893689 | 26.56 | 7.35 | 12.24 | 54.35 |
| cost of materials ($1$m$) | 1893689 | 61328.05 | 162337.03 | 271.20 | 690771.20 |
| industry value added (output) ($100$m$) | 1893689 | 177.13 | 272.06 | 3.00 | 1180.37 |
| output per hour ($1000) | 1893689 | 2.62 | 2.82 | 0.44 | 34.28 |
| output per worker ($1000) | 1893689 | 3.65 | 3.99 | 0.63 | 44.31 |
| industry profits ($1m) | 1893689 | 14808.95 | 24171.54 | 196.20 | 111886.80 |

NOTES: Intensity denotes per $100 mil

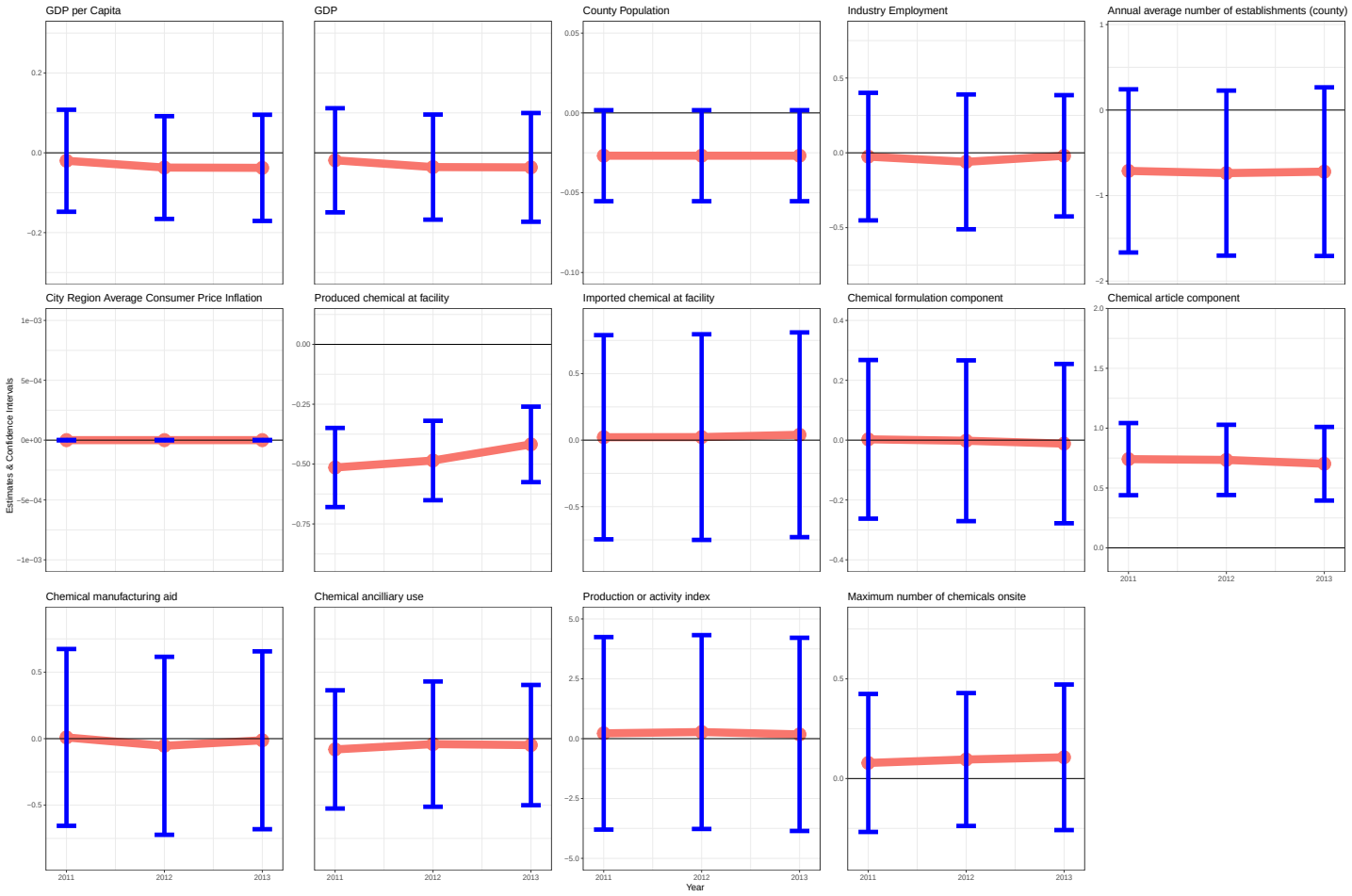



Figure 7: County-level Macroeconomic Trends in Border Counties

NOTES: This figure is obtained from estimating this equation $y_{cp,t} = \sum_{t=2011}^{2013} \beta(Treated \cdot B)_{s,t} + \lambda_t + \delta_h + \zeta_{cp,t} + \epsilon_{cp,t}$. Where $y_{cp,t}$ is the vector of observables. Treated is the grouping variable that is unity for the treated states and zero for the control states. $B_t$ is a dummy variable with three levels of time: 2011, 2012, and 2013. $\beta$ is the parameter vector of coefficients. $\zeta_{cp,t}$ is the border-county-pair-year fixed effects. $\epsilon_{cp,t}$ is the error term. Robust standard errors are clustered at the state level.

Table 14: Treatment Selection

| $Treated^e$ | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| GDP (lagged) | -0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) |
| GDP per capita (lagged) | 0.001 (0.002) | 0.001 (0.002) | 0.001 (0.002) | 0.001 (0.002) | -0.002 (0.002) |
| Personal income (lagged) | 0.000 (0.000) | 0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| Average number of establishments (lagged) | -0.001 (0.001) | -0.000 (0.001) | -0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| Inflation (lagged) | 0.010 (0.007) | NA | NA | NA | NA |
| Entire Facility (0,1) | -0.637*** (0.149) | -0.654*** (0.144) | 0.015 (0.069) | 0.015 (0.069) | 0.006 (0.005) |
| Private Facility (0,1) | 0.094 (0.060) | 0.094 (0.059) | 0.008 (0.005) | 0.008 (0.005) | 0.004 (0.003) |
| Federal Facility (0,1) | -0.082 (0.074) | -0.082 (0.074) | 0.001 (0.031) | 0.001 (0.031) | -0.011 (0.008) |
| controls | Yes | Yes | Yes | Yes | Yes |
| year FE | No | Yes | Yes | Yes | Yes |
| county FE | No | No | Yes | Yes | Yes |
| border-county pair × year FEs | No | No | No | No | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.082 | 0.110 | 0.616 | 0.616 | 0.952 |

NOTES: Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

Table 15: Manufacturing Industry Costs: Alternative Clustering of the SEs

| | Hourly Wage | | | | Total Payroll (log) | | | | Material Cost (log) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| industry costs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| $Treated^e$ | 0.892** | 0.892** | 0.892** | 0.892** | 0.044* | 0.044 | 0.044 | 0.044 | 0.130* | 0.130* | 0.130* | 0.130* |
| | (0.449) | (0.403) | (0.426) | (0.415) | (0.025) | (0.038) | (0.034) | (0.037) | (0.071) | (0.069) | (0.072) | (0.072) |
| cohort 2014 | 1.200* | 1.200** | 1.200* | 1.200* | 0.004 | 0.004 | 0.004 | 0.004* | 0.187* | 0.187* | 0.187* | 0.187* |
| | (0.707) | (0.592) | (0.656) | (0.629) | (0.037) | (0.049) | (0.044) | (0.049) | (0.108) | (0.107) | (0.106) | (0.106) |
| cohort 2015 | 0.390** | 0.390 | 0.390 | 0.390 | 0.114*** | 0.114* | 0.114** | 0.114* | 0.034 | 0.034 | 0.034 | 0.034 |
| | (0.192) | (0.378) | (0.313) | (0.356) | (0.030) | (0.065) | (0.053) | (0.058) | (0.060) | (0.077) | (0.074) | (0.074) |
| cohort 2017 | -0.205 | -0.205 | -0.205 | -0.205 | -0.612*** | -0.612*** | -0.612*** | -0.612*** | -0.343*** | -0.343 | -0.343* | -0.343* |
| | (0.437) | (1.270) | (1.000) | (0.996) | (0.166) | (0.199) | (0.199) | (0.200) | (0.131) | (0.212) | (0.181) | (0.180) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| county FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| border-county pair × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| clustered at the: | county | industry | zipcode | facility | county | industry | zipcode | facility | county | industry | zipcode | facility |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.624 | 0.624 | 0.624 | 0.624 | 0.440 | 0.440 | 0.440 | 0.440 | 0.619 | 0.619 | 0.619 | 0.619 |

NOTES: These results are obtained from estimating model 1. Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.




Figure 8: Proportion of Low and High Skilled Workers in Manufacturing Industries

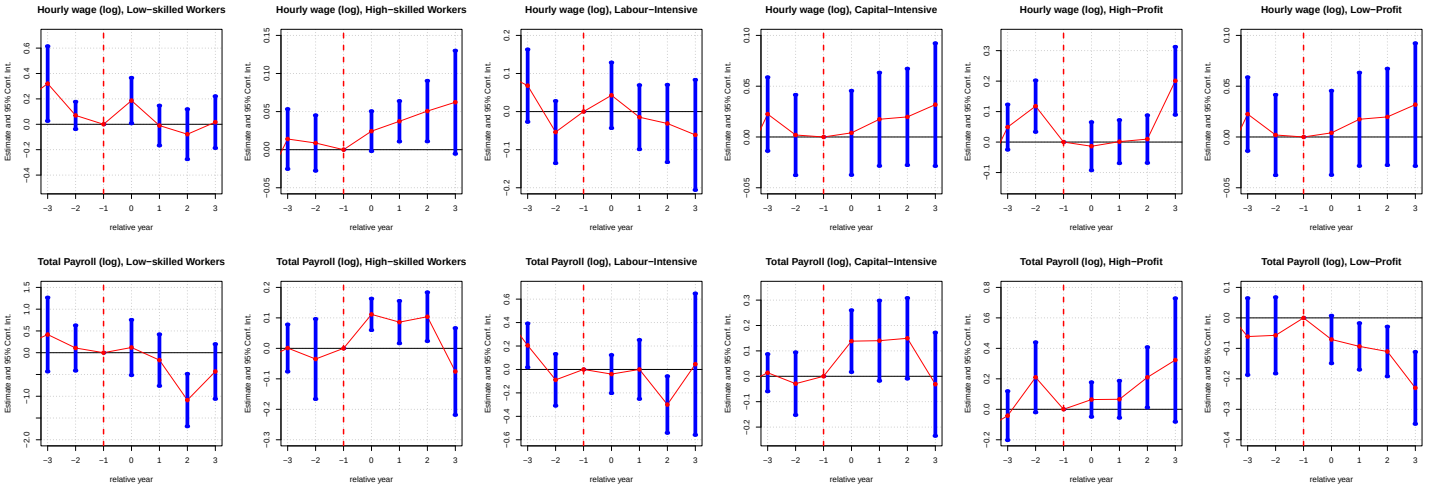



Figure 9: Heterogeneous Effects of the MW Policy on Manufacturing Industry Costs

NOTES: The event study model of equation 1 is $C_{i,cp,t} = \sum_{e=-3, e\neq -1}^{3} \beta(Treated^e \cdot D)_{i,s,t} + \psi(Treated^e)_{s,t} + \vartheta(Treated \cdot D)_{i,s,t} + \mu(Post \cdot D)_{i,s,t} + \tau Treated_{s,t} + \rho D_{i,s,t} + \alpha Post_t + \sigma X_{v,h,t-1} + \omega F_{f,t} + \delta_h + \zeta_{cp,t} + \epsilon_{i,cp,t}$. Standard errors are clustered at the state level. $D_{i,s,t}$ is unity for low-skilled and zero for high-skilled workers; $Treated_{s,t}$ is unity for treated and zero for control states; and $Post_t$ is unity for post-treatment and zero for pre-treatment periods.

## II. List of Toxic Chemicals, and Robustness

Table 16: Analyzed Chemicals

| chemical name | classification | attribute | onsite | offsite | potw | chemical name | classification | attribute | onsite | offsite | potw |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1-Chloro-1,1-difluoroethane (HCFC-142b) | TRI | formulation component | yes | NA | NA | Dimethylamine dicamba | TRI | others | yes | NA | NA |
| 1,2-Dibromoethane | TRI | carcinogenic | yes | yes | NA | Dioxin and dioxin-like compounds | DIOXIN | carcinogenic | yes | yes | NA |
| 1,2-Dichloroethane | TRI | carcinogenic | yes | yes | NA | Epichlorohydrin | TRI | carcinogenic | yes | yes | NA |
| 1,2,4-Trimethylbenzene | TRI | formulation component | yes | yes | yes | Ethyl acrylate | TRI | carcinogenic | yes | yes | yes |
| 1,3-Butadiene | TRI | carcinogenic | yes | NA | NA | Ethylbenzene | TRI | carcinogenic | yes | yes | yes |
| 1,3-Phenylenediamine | TRI | formulation component | yes | NA | NA | Ethylene | TRI | formulation component | yes | NA | NA |
| 1,4-Dioxane | TRI | carcinogenic | yes | yes | NA | Ethylene glycol | TRI | clean air act | yes | yes | yes |
| 2-Ethoxyethanol | TRI | formulation component | yes | yes | NA | Ethylene oxide | TRI | carcinogenic | yes | NA | NA |
| 2-Phenylphenol | TRI | formulation component | yes | NA | NA | Fomesafen | TRI | formulation component | yes | yes | yes |
| 2,2-Bis(bromomethyl)-1,3-propanediol | TRI | carcinogenic | yes | NA | NA | Formaldehyde | TRI | carcinogenic | yes | yes | yes |
| 2,2-Dichloro-1,1,1-trifluoroethane (HCFC-123) | TRI | manufacturing aid | yes | yes | NA | Formic acid | TRI | formulation component | yes | yes | NA |
| 2,4-D | TRI | carcinogenic | yes | yes | NA | Hexachlorobenzene | PBT | carcinogenic | yes | yes | yes |
| 2,4-D 2-ethylhexyl ester | TRI | carcinogenic | yes | yes | NA | Hydrazine | TRI | carcinogenic | yes | NA | NA |
| 2,4-Dimethylphenol | TRI | ancillary use | yes | NA | NA | Hydrochloric acid (acid aerosols including mists, vapors, gas, fog, and other airborne forms of any particle size) | TRI | clean air act | yes | NA | NA |
| 2,4-Dinitrotoluene | TRI | carcinogenic | yes | NA | NA | Hydrogen cyanide | TRI | article component | yes | yes | NA |
| 2,6-Dinitrotoluene | TRI | carcinogenic | yes | NA | NA | Hydrogen fluoride | TRI | clean air act | yes | yes | yes |
| 3-Iodo-2-propynyl butylcarbamate | TRI | formulation component | yes | yes | NA | Hydroquinone | TRI | clean air act | yes | yes | yes |
| 4,4'-Isopropylidenediphenol | TRI | formulation component | yes | yes | NA | Lead | PBT | carcinogenic | yes | yes | yes |
| Acetaldehyde | TRI | carcinogenic | yes | yes | NA | Lead compounds | PBT | clean air act | yes | yes | yes |
| Acetonitrile | TRI | clean air act | yes | yes | NA | Lithium carbonate | TRI | metal restricted | yes | yes | NA |
| Acetophenone | TRI | clean air act | yes | yes | NA | Maleic anhydride | TRI | clean air act | yes | yes | yes |
| Acrolein | TRI | clean air act | yes | NA | NA | Manganese | TRI | clean air act | yes | yes | yes |
| Acrylamide | TRI | carcinogenic | yes | yes | NA | Manganese compounds | TRI | clean air act | yes | yes | yes |
| Acrylic acid | TRI | clean air act | yes | yes | NA | Mercury | PBT | clean air act | yes | yes | yes |
| Acrylonitrile | TRI | carcinogenic | yes | yes | yes | Mercury compounds | PBT | clean air act | yes | yes | yes |
| Allyl alcohol | TRI | article component | yes | yes | NA | Methanol | TRI | clean air act | yes | yes | yes |
| Aluminum (fume or dust) | TRI | metal restricted | yes | yes | NA | Methoxone | TRI | carcinogenic | yes | NA | NA |
| Aluminum oxide (fibrous forms) | TRI | metal restricted | yes | yes | NA | Methyl acrylate | TRI | formulation component | yes | yes | NA |
| Ammonia | TRI | formulation component | yes | yes | yes | Methyl isobutyl ketone | TRI | carcinogenic | yes | yes | yes |
| Anthracene | TRI | formulation component | yes | yes | yes | Methyl methacrylate | TRI | clean air act | yes | yes | yes |
| Antimony | TRI | clean air act | yes | yes | yes | Methyl tert-butyl ether | TRI | clean air act | yes | yes | yes |
| Antimony compounds | TRI | clean air act | yes | yes | yes | Molybdenum trioxide | TRI | metal restricted | yes | yes | NA |
| Arsenic | TRI | carcinogenic | yes | NA | NA | n-Butyl alcohol | TRI | formulation component | yes | yes | yes |
| Arsenic compounds | TRI | clean air act | yes | yes | NA | n-Hexane | TRI | clean air act | yes | yes | yes |
| Asbestos (friable) | TRI | carcinogenic | yes | NA | NA | N-Methyl-2-pyrrolidone | TRI | formulation component | yes | yes | yes |
| Atrazine | TRI | formulation component | yes | yes | yes | N-Methylolacrylamide | TRI | others | yes | yes | NA |
| Barium | TRI | metal restricted | yes | NA | NA | N,N-Dimethylaniline | TRI | clean air act | yes | NA | NA |
| Barium compounds (except for barium sulfate (CAS No. 7727-43-7)) | TRI | metal restricted | yes | yes | yes | N,N-Dimethylformamide | TRI | clean air act | yes | yes | yes |
| Benzal chloride | TRI | others | yes | yes | NA | Naphthalene | TRI | carcinogenic | yes | yes | yes |
| Benzene | TRI | carcinogenic | yes | yes | yes | Nickel | TRI | carcinogenic | yes | yes | yes |
| Benzo[g,h,i]perylene | PBT | clean air act | yes | yes | yes | Nickel compounds | TRI | carcinogenic | yes | yes | yes |
| Benzoyl peroxide | TRI | formulation component | yes | yes | NA | Nitrate compounds (water dissociable; reportable only when in aqueous solution) | TRI | formulation component | yes | yes | yes |
| Benzyl chloride | TRI | clean air act | yes | NA | NA | Nitric acid | TRI | formulation component | yes | yes | yes |
| Biphenyl | TRI | clean air act | yes | NA | NA | Nitrobenzene | TRI | carcinogenic | yes | NA | NA |
| Boron trichloride | TRI | metal restricted | yes | NA | NA | o-Xylene | TRI | clean air act | yes | yes | NA |
| Bromomethane | TRI | clean air act | yes | NA | NA | Ozone | TRI | ancillary use | yes | NA | NA |
| Butyl acrylate | TRI | formulation component | yes | yes | yes | p-Xylene | TRI | clean air act | yes | NA | NA |
| Cadmium | TRI | carcinogenic | yes | yes | NA | Pentachlorophenol | TRI | carcinogenic | yes | yes | NA |
| Cadmium compounds | TRI | carcinogenic | yes | yes | yes | Peracetic acid | TRI | formulation component | yes | yes | NA |
| Carbon disulfide | TRI | clean air act | yes | NA | NA | Phenanthrene | TRI | clean air act | yes | yes | yes |
| Carbonyl sulfide | TRI | clean air act | yes | NA | NA | Phenol | TRI | clean air act | yes | yes | yes |
| Catechol | TRI | carcinogenic | yes | NA | NA | Phosphorus (yellow or white) | TRI | clean air act | yes | NA | NA |
| Certain glycol ethers | TRI | clean air act | yes | yes | yes | Phthalic anhydride | TRI | clean air act | yes | yes | yes |
| Chlorine | TRI | clean air act | yes | NA | NA | Polychlorinated biphenyls | PBT | carcinogenic | yes | NA | NA |
| Chlorine dioxide | TRI | article component | yes | NA | NA | Polycyclic aromatic compounds | PBT | carcinogenic | yes | yes | yes |
| Chlorobenzene | TRI | clean air act | yes | yes | NA | Propiconazole | TRI | formulation component | yes | yes | yes |
| Chloroethane | TRI | clean air act | yes | yes | NA | Propylene | TRI | formulation component | yes | yes | NA |
| Chloroform | TRI | carcinogenic | yes | yes | yes | Propylene oxide | TRI | carcinogenic | yes | NA | NA |
| Chloromethane | TRI | clean air act | yes | NA | NA | Pyridine | TRI | article component | yes | yes | NA |
| Chromium | TRI | clean air act | yes | yes | yes | sec-Butyl alcohol | TRI | formulation component | yes | yes | yes |
| Chromium compounds (except for chromite ore mined in the Transvaal Region) | TRI | clean air act | yes | yes | yes | Selenium compounds | TRI | clean air act | yes | yes | NA |
| Cobalt | TRI | carcinogenic | yes | yes | yes | Silver | TRI | metal restricted | yes | yes | yes |
| Cobalt compounds | TRI | clean air act | yes | yes | yes | Silver compounds | TRI | metal restricted | yes | yes | yes |
| Copper | TRI | metal restricted | yes | yes | yes | Sodium dimethyldithiocarbamate | TRI | formulation component | yes | NA | NA |
| Copper compounds | TRI | metal restricted | yes | yes | yes | Sodium nitrite | TRI | metal restricted | yes | yes | yes |
| Creosote | TRI | carcinogenic | yes | yes | NA | Styrene | TRI | carcinogenic | yes | yes | yes |
| Cresol (mixed isomers) | TRI | clean air act | yes | yes | NA | Sulfuric acid (acid aerosols including mists, vapors, gas, fog, and other airborne forms of any particle size) | TRI | formulation component | yes | NA | NA |
| Cumene | TRI | carcinogenic | yes | yes | NA | tert-Butyl alcohol | TRI | formulation component | yes | NA | NA |
| Cumene hydroperoxide | TRI | manufacturing aid | yes | yes | NA | Tetrabromobisphenol A | PBT | formulation component | yes | yes | yes |
| Cyanide compounds | TRI | clean air act | yes | yes | yes | Tetrachloroethylene | TRI | carcinogenic | yes | yes | NA |
| Cyclohexane | TRI | formulation component | yes | yes | yes | Thiabendazole | TRI | formulation component | yes | yes | yes |
| Decabromodiphenyl oxide | TRI | formulation component | yes | yes | NA | Thiram | TRI | article component | yes | yes | yes |
| Di(2-ethylhexyl) phthalate | TRI | carcinogenic | yes | yes | yes | Toluene | TRI | clean air act | yes | yes | yes |
| Diaminotoluene (mixed isomers) | TRI | carcinogenic | yes | NA | NA | Toluene-2,4-diisocyanate | TRI | carcinogenic | yes | yes | NA |
| Dibenzofuran | TRI | clean air act | yes | yes | NA | Toluene diisocyanate (mixed isomers) | TRI | carcinogenic | yes | yes | NA |
| Dibutyl phthalate | TRI | clean air act | yes | NA | NA | Trichloroethylene | TRI | carcinogenic | yes | yes | NA |
| Dichloromethane | TRI | carcinogenic | yes | yes | yes | Triethylamine | TRI | clean air act | yes | yes | NA |
| Dicyclopentadiene | TRI | formulation component | yes | yes | yes | Trifluralin | PBT | clean air act | yes | NA | NA |
| Diethanolamine | TRI | clean air act | yes | yes | NA | Vanadium compounds | TRI | metal restricted | yes | yes | NA |
| Diglycidyl resorcinol ether | TRI | carcinogenic | yes | NA | NA | Vinyl acetate | TRI | carcinogenic | yes | yes | NA |
| Diisocyanates | TRI | clean air act | yes | yes | NA | Vinyl chloride | TRI | carcinogenic | yes | yes | NA |
| Dimethyl phthalate | TRI | clean air act | yes | yes | NA | Xylene (mixed isomers) | TRI | clean air act | yes | yes | yes |
| Dimethylamine | TRI | formulation component | yes | yes | NA | Zinc (fume or dust) | TRI | metal restricted | yes | yes | NA |
| Dimethylamine dicamba | TRI | others | yes | NA | NA | Zinc compounds | TRI | metal restricted | yes | yes | yes |

NOTES: NA means absent in that sample; POTW means publicly owned treatment works.

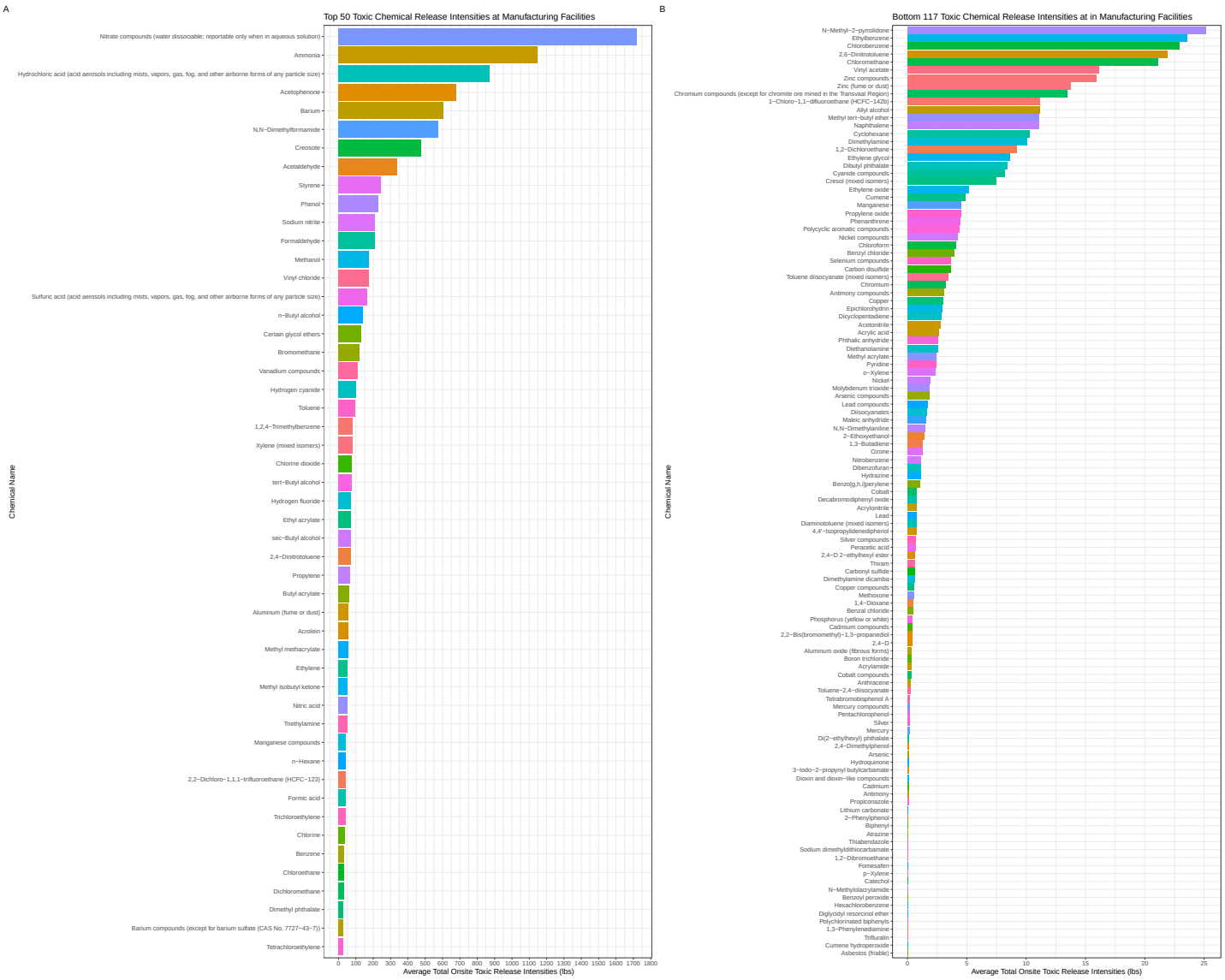



Figure 10: Toxic Chemical Release Intensities at Onsite Manufacturing Facilities

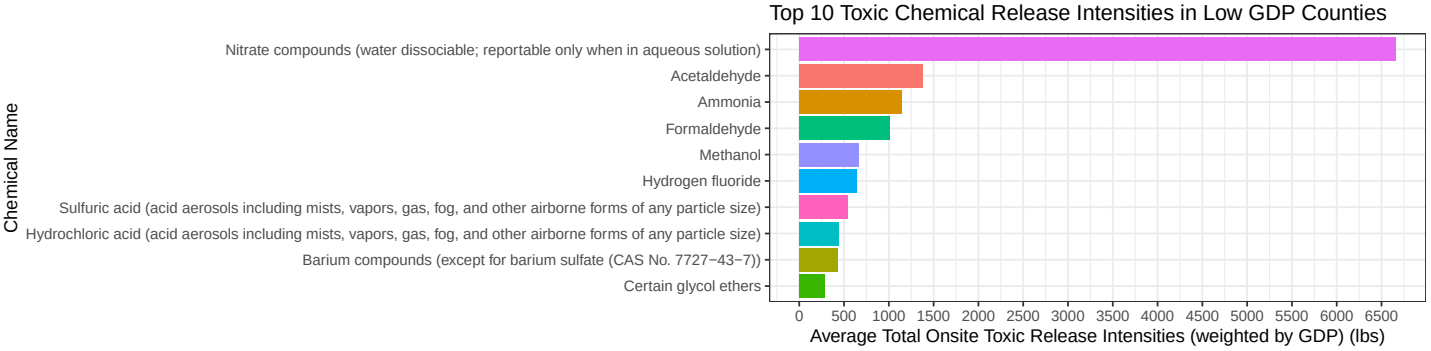



Figure 11: Post-treatment Toxic Chemical Release Intensities at Onsite Manufacturing Facilities, in Low GDP counties

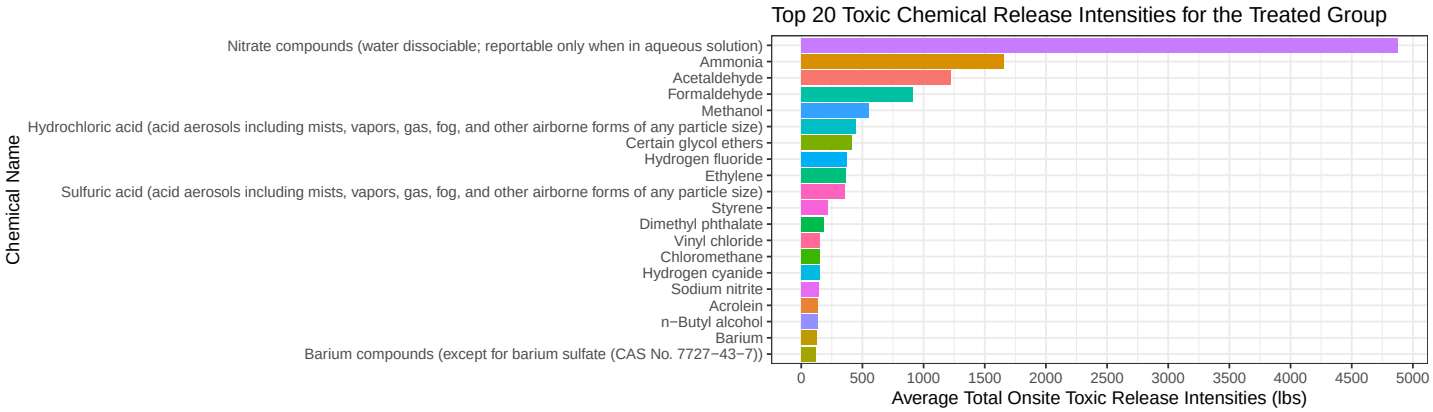



Figure 12: Post-treatment Total Onsite Toxic Chemical Release Intensities at Manufacturing Facilities

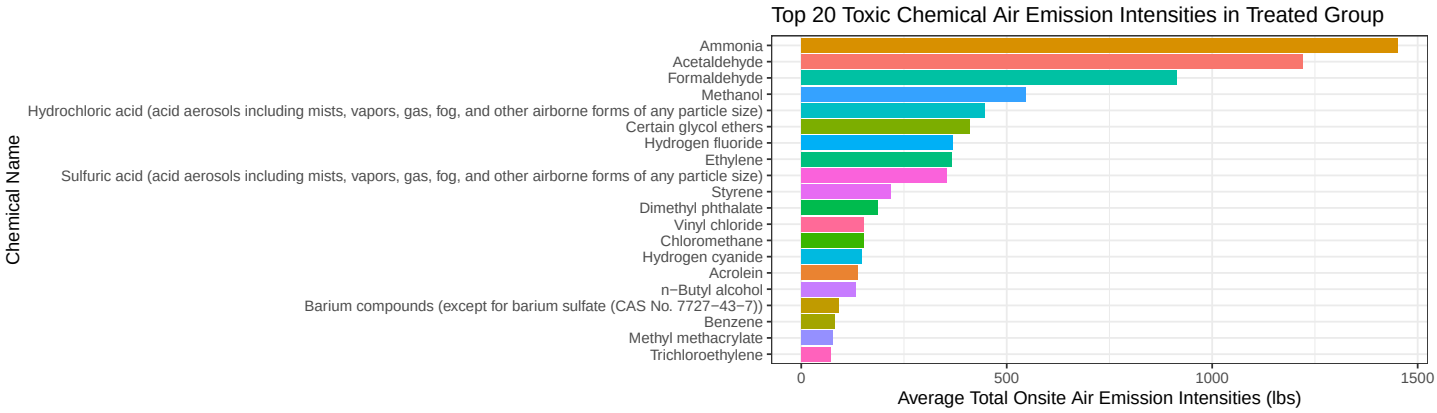



Figure 13: Post-treatment Total Onsite Toxic Air Emission Intensities at Manufacturing Facilities

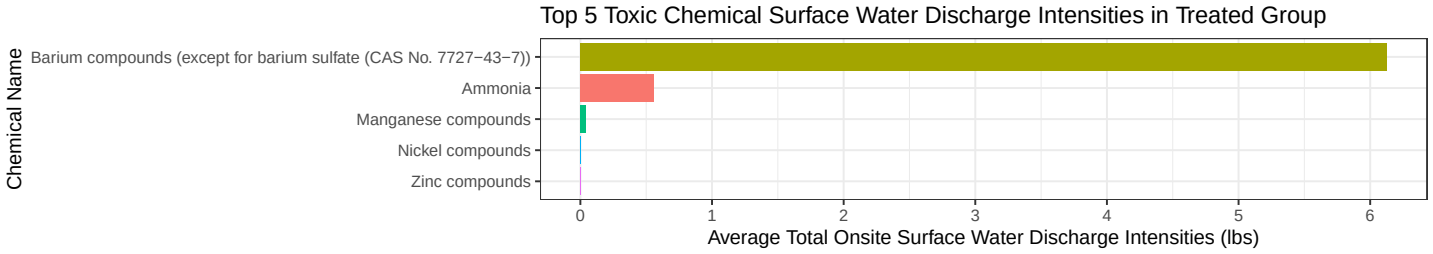



Figure 14: Post-treatment Total Onsite Surface Water Discharge Intensities at Manufacturing Facilities

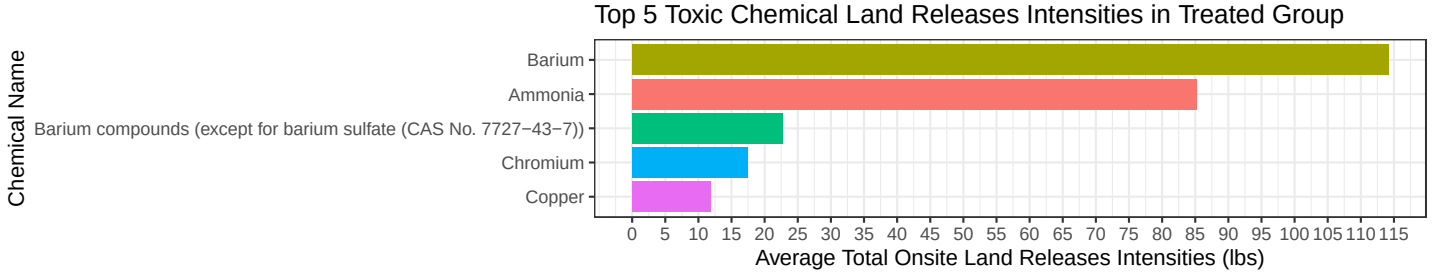



Figure 15: Post-treatment Total Onsite Land Release Intensities at Manufacturing Facilities

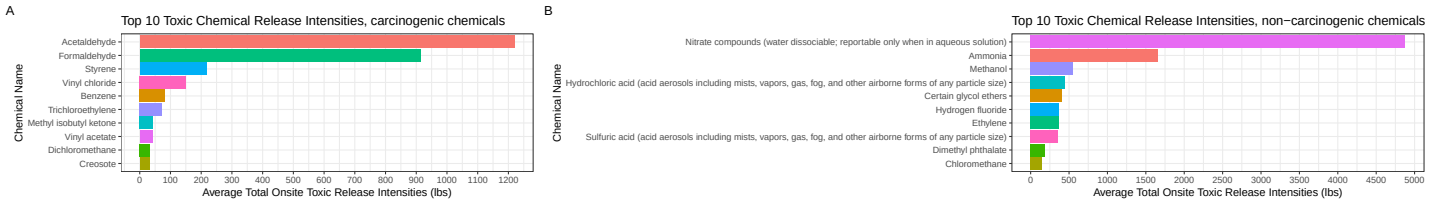



Figure 16: Post-treatment Carcinogenic Chemical Release Intensities at Onsite Manufacturing Facilities

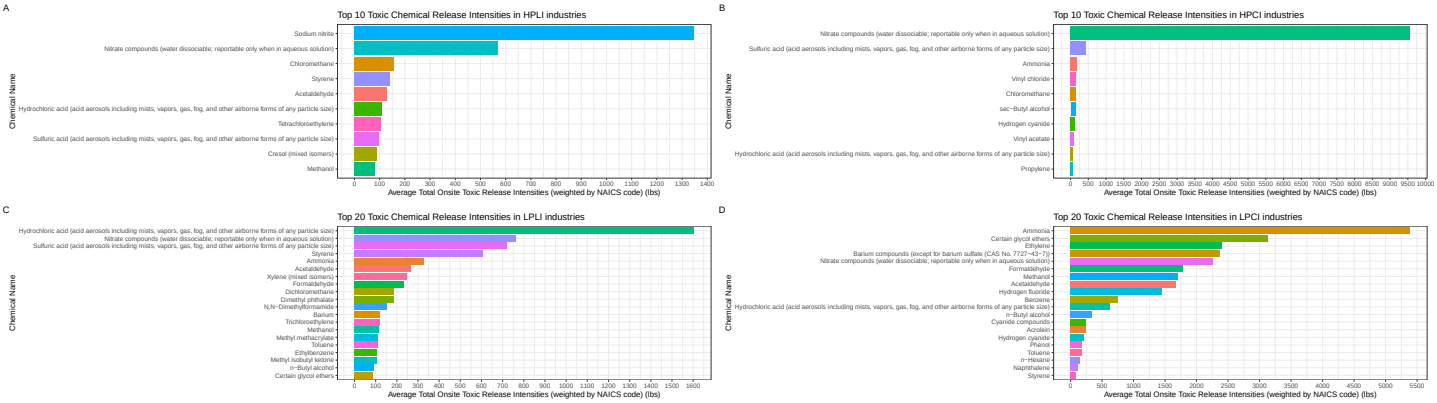



Figure 17: Post-treatment Total Onsite Toxic Chemical Release Intensities, for HPLI, HPCI, LPLI, and LPCI Manufacturing Facilities

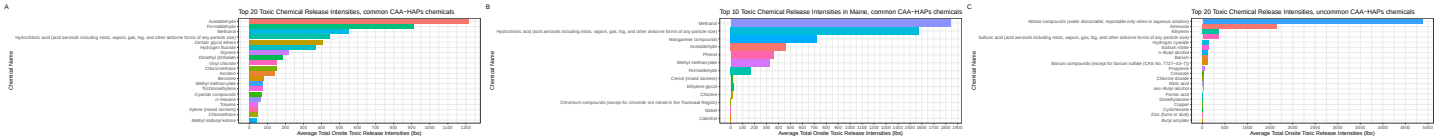



Figure 18: Post-treatment CAA and HAPs Chemical Release Intensities at Onsite Manufacturing Facilities

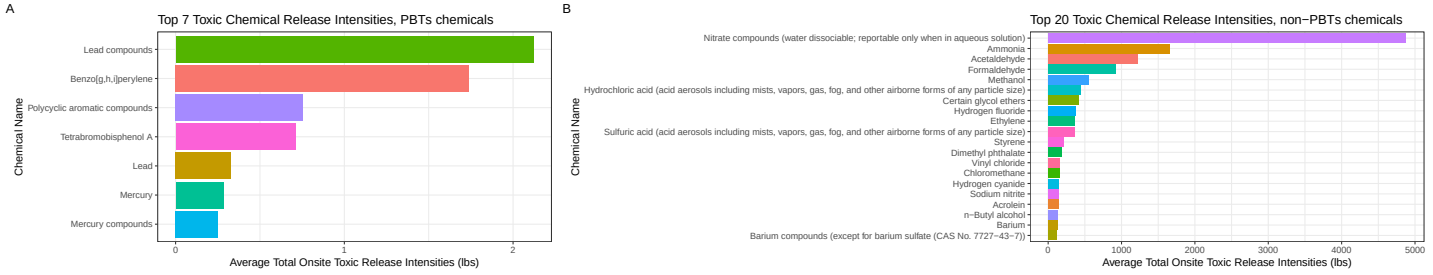



Figure 19: Post-treatment PBTs Chemical Release Intensities at Onsite Manufacturing Facilities

Table 17: Effect of the MW policy on Total Onsite Toxic Releases Intensity, from Catastrophic Events

| Total release intensity, from catastrophic events (log) | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $Treated^e$ | -0.414*** | 0.008 | 0.004 | -0.017 |
| | (0.052) | (0.049) | (0.050) | (0.057) |
| controls | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes |
| facility FE | No | Yes | Yes | Yes |
| toxic chemical × year FEs | No | No | Yes | Yes |
| border-county pair × year FEs | No | No | No | Yes |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.269 | 0.774 | 0.803 | 0.818 |
| Baseline Mean | 4.36 | 4.36 | 4.36 | 4.36 |

NOTES: These results are obtained from estimating model 7. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

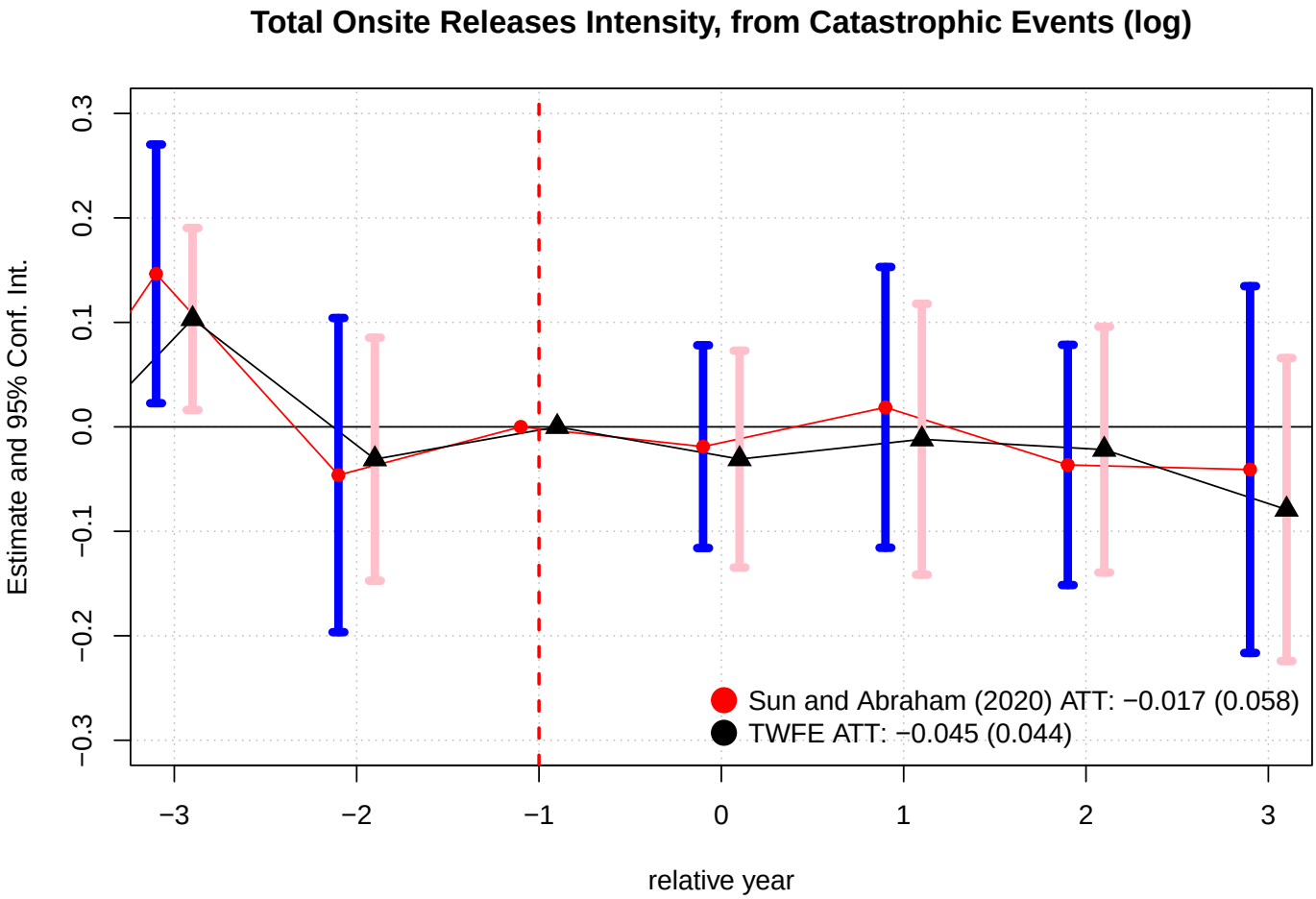



Figure 20: Total Onsite Releases Intensity, from Catastrophic Events

NOTES: The event study model of equation 7 is $P^{catastrophic}_{f,cp,c,t} = \sum_{e=-5, e\neq -1}^{3} \beta Treated^e_{s,t} + \sigma X_{v,h,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}$. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. The test for the presence of pre-trends shows and F-statistic of 0.6159 (0.7349), p-value (in parentheses) using F-Statistic ($\chi^2$) : $\sum_{-3}^{-2} \beta_e = 0$. de Chaisemartin and D'Haultfoeuille Decomposition: $\sum dCDH^{weights(+)}_{ATTs} = 1$ and $\sum dCDH^{weights(-)}_{ATTs} = 0$.

Table 18: Total Onsite Releases Intensity: Alternative clustering of the SEs

| Total releases intensity (log) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Treated*$^e$ | 0.110*** | 0.110*** | 0.110** | 0.110** | 0.110*** | 0.110* | 0.110** | 0.110** | 0.110*** | 0.110*** | 0.110*** | 0.110*** |
| | (0.042) | (0.041) | (0.043) | (0.044) | (0.041) | (0.056) | (0.055) | (0.055) | (0.041) | (0.041) | (0.042) | (0.044) |
| cohort 2014 | 0.100* | 0.100** | 0.100** | 0.100 | 0.100** | 0.100 | 0.100 | 0.100 | 0.100** | 0.100** | 0.100* | 0.100** |
| | (0.054) | (0.052) | (0.058) | (0.063) | (0.048) | (0.079) | (0.078) | (0.077) | (0.048) | (0.048) | (0.054) | (0.063) |
| cohort 2015 | 0.126* | 0.126* | 0.126* | 0.126* | 0.126** | 0.126 | 0.126 | 0.126 | 0.126** | 0.126** | 0.126* | 0.126* |
| | (0.072) | (0.071) | (0.068) | (0.064) | (0.050) | (0.079) | (0.077) | (0.077) | (0.050) | (0.050) | (0.072) | (0.064) |
| cohort 2017 | 0.238* | 0.238* | 0.238 | 0.238** | 0.238** | 0.238** | 0.238*** | 0.238*** | 0.238** | 0.238** | 0.238* | 0.238** |
| | (0.127) | (0.129) | (0.144) | (0.116) | (0.106) | (0.075) | (0.074) | (0.074) | (0.106) | (0.106) | (0.127) | (0.116) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| border-county pair × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| clustered at the: | facility | zipcode | county | industry | chemical | state | facility & chemical | facility & industry | chemical & industry | chemical & state | facility & state | industry & state |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 | 0.726 |

NOTES: These results are obtained from estimating model 2. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

Table 19: Total Onsite Air Emissions Intensity: Alternative clustering of the SEs

| Total air emissions intensity (log) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Treated*$^e$ | 0.092*** | 0.092*** | 0.092** | 0.092** | 0.092*** | 0.092* | 0.092*** | 0.092*** | 0.092*** | 0.092*** | 0.092*** | 0.092** |
| | (0.035) | (0.035) | (0.037) | (0.037) | (0.032) | (0.048) | (0.035) | (0.035) | (0.032) | (0.032) | (0.035) | (0.037) |
| cohort 2014 | 0.121** | 0.121** | 0.121** | 0.121** | 0.121*** | 0.121* | 0.121** | 0.121** | 0.121*** | 0.121*** | 0.121** | 0.121* |
| | (0.048) | (0.048) | (0.053) | (0.057) | (0.046) | (0.068) | (0.048) | (0.048) | (0.046) | (0.046) | (0.048) | (0.057) |
| cohort 2015 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 |
| | (0.058) | (0.058) | (0.056) | (0.054) | (0.044) | (0.062) | (0.058) | (0.058) | (0.044) | (0.044) | (0.058) | (0.054) |
| cohort 2017 | 0.118 | 0.118 | 0.118 | 0.118 | 0.118 | 0.118* | 0.118 | 0.118 | 0.118 | 0.118 | 0.118 | 0.118 |
| | (0.098) | (0.100) | (0.099) | (0.101) | (0.097) | (0.060) | (0.098) | (0.098) | (0.096) | (0.097) | (0.098) | (0.101) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| border-county pair × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| clustered at the: | facility | zipcode | county | industry | chemical | state | facility & chemical | facility & industry | chemical & industry | chemical & state | facility & state | industry & state |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 | 0.745 |

NOTES: These results are obtained from estimating model 3. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

Table 20: Total Onsite Surface Water Discharge Intensity: Alternative clustering of the SEs

| Total surface water discharge intensity (log) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Treated*$^e$ | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 | 0.013 |
| | (0.022) | (0.022) | (0.021) | (0.024) | (0.031) | (0.020) | (0.022) | (0.022) | (0.031) | (0.031) | (0.022) | (0.024) |
| cohort 2014 | -0.054** | -0.054** | -0.054** | -0.054* | -0.054 | -0.054** | -0.054** | -0.054** | -0.054* | -0.054* | -0.054** | -0.054* |
| | (0.024) | (0.024) | (0.023) | (0.028) | (0.030) | (0.020) | (0.024) | (0.024) | (0.030) | (0.030) | (0.024) | (0.028) |
| cohort 2015 | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** |
| | (0.037) | (0.038) | (0.039) | (0.035) | (0.046) | (0.039) | (0.037) | (0.037) | (0.046) | (0.046) | (0.037) | (0.035) |
| cohort 2017 | 0.096 | 0.096 | 0.096* | 0.096** | 0.096** | 0.096** | 0.096 | 0.096 | 0.096** | 0.096** | 0.096 | 0.096** |
| | (0.059) | (0.058) | (0.051) | (0.046) | (0.042) | (0.042) | (0.059) | (0.059) | (0.041) | (0.042) | (0.059) | (0.046) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| border-county pair × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| clustered at the: | facility | zipcode | county | industry | chemical | state | facility & chemical | facility & industry | chemical & industry | chemical & state | facility & state | industry & state |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 | 0.592 |

NOTES: These results are obtained from estimating model 4. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

Table 21: Total Onsite Land Releases Intensity: Alternative Clustering of SEs

| Total onsite land releases intensity (log) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Treated*$^e$ | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 | -0.013 |
| | (0.022) | (0.021) | (0.019) | (0.019) | (0.016) | (0.010) | (0.022) | (0.022) | (0.016) | (0.016) | (0.022) | (0.019) |
| cohort 2020 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 | -0.009 |
| | (0.033) | (0.032) | (0.030) | (0.030) | (0.024) | (0.012) | (0.033) | (0.033) | (0.024) | (0.024) | (0.033) | (0.030) |
| cohort 2015 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 |
| | (0.022) | (0.022) | (0.015) | (0.020) | (0.021) | (0.017) | (0.022) | (0.022) | (0.021) | (0.021) | (0.022) | (0.020) |
| cohort 2017 | 0.078* | 0.078* | 0.078* | 0.078* | 0.078* | 0.078*** | 0.078* | 0.078* | 0.078** | 0.078** | 0.078* | 0.078** |
| | (0.047) | (0.047) | (0.039) | (0.033) | (0.034) | (0.016) | (0.047) | (0.047) | (0.034) | (0.034) | (0.047) | (0.033) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| toxic chemical × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| border county pair × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| clustered at the: | facility | zipcode | county | industry | chemical | state | facility & chemical | facility & industry | chemical & industry | chemical & state | facility & state | industry & state |
| Observations | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 | 0.506 |

NOTES: These results are obtained from estimating model 5. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively.

## III. Distribution of Industries and Pollution Emissions Intensities

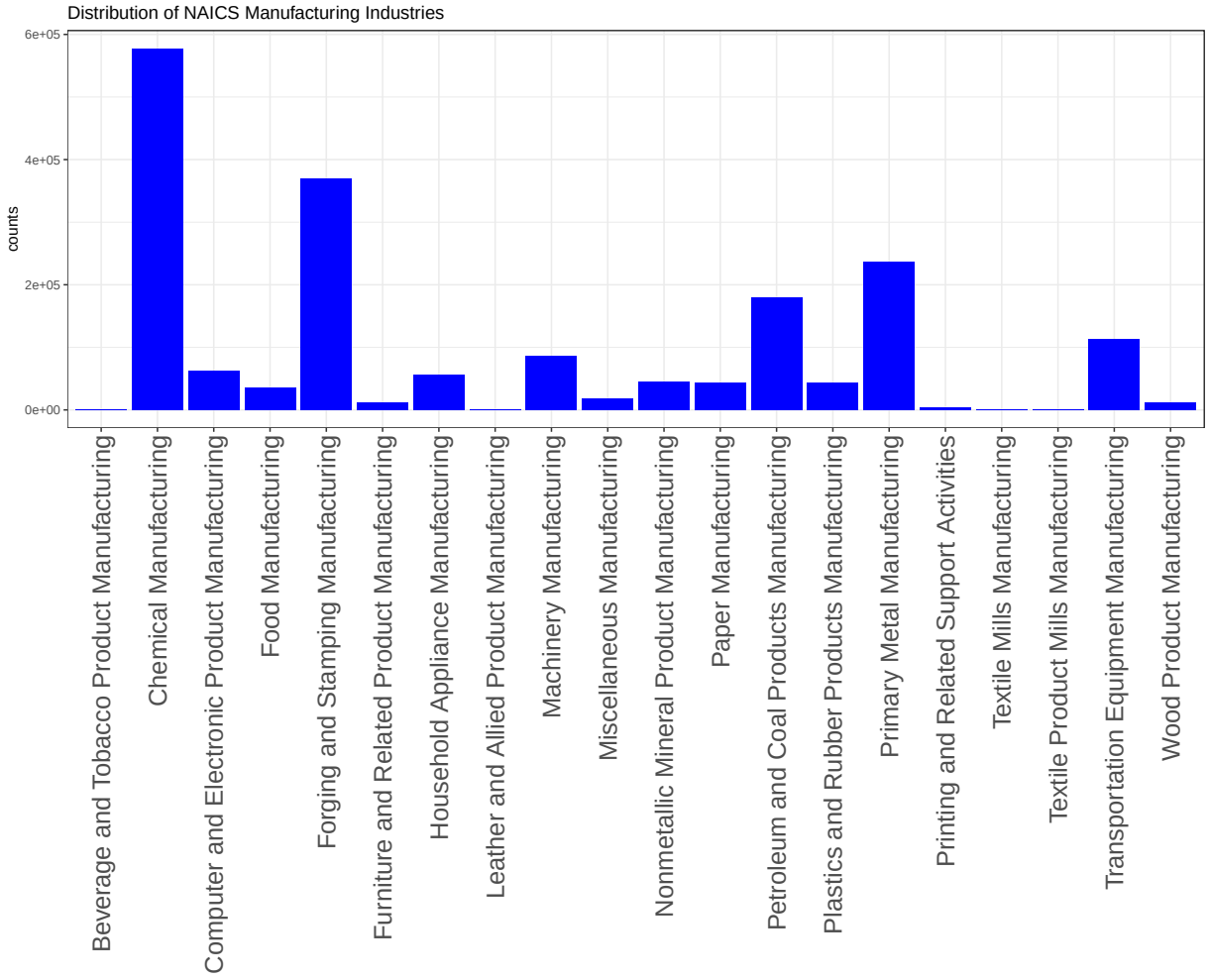



Figure 21: Distribution of Manufacturing Industries in the Sample

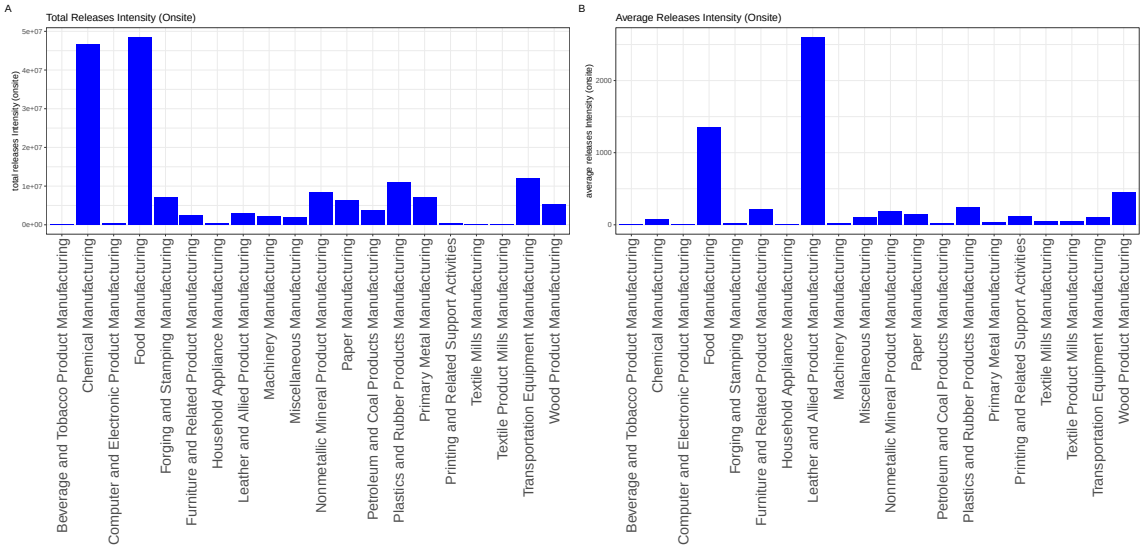



Figure 22: Distribution of Total Onsite Releases Intensity across Manufacturing Industries

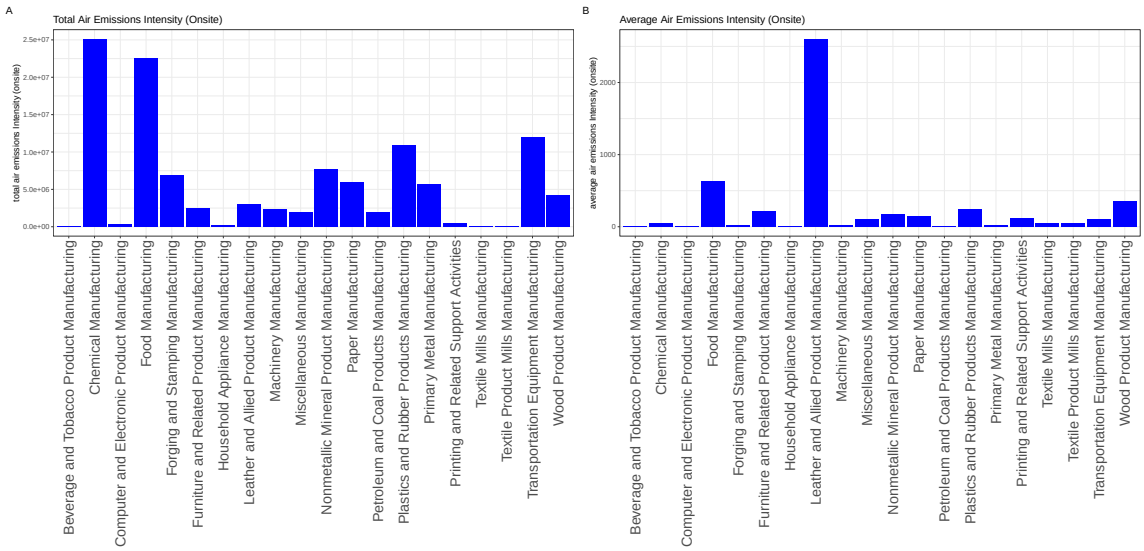



Figure 23: Distribution of Total Onsite Air Emissions Intensity across Manufacturing Industries

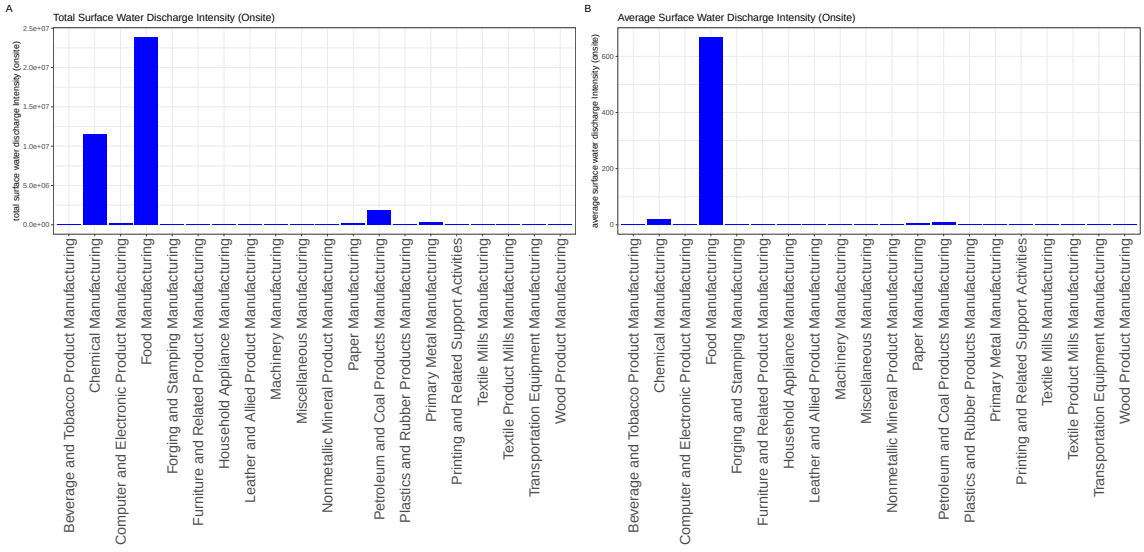



Figure 24: Distribution of Total Onsite Surface Water Discharge Intensity across Manufacturing Industries

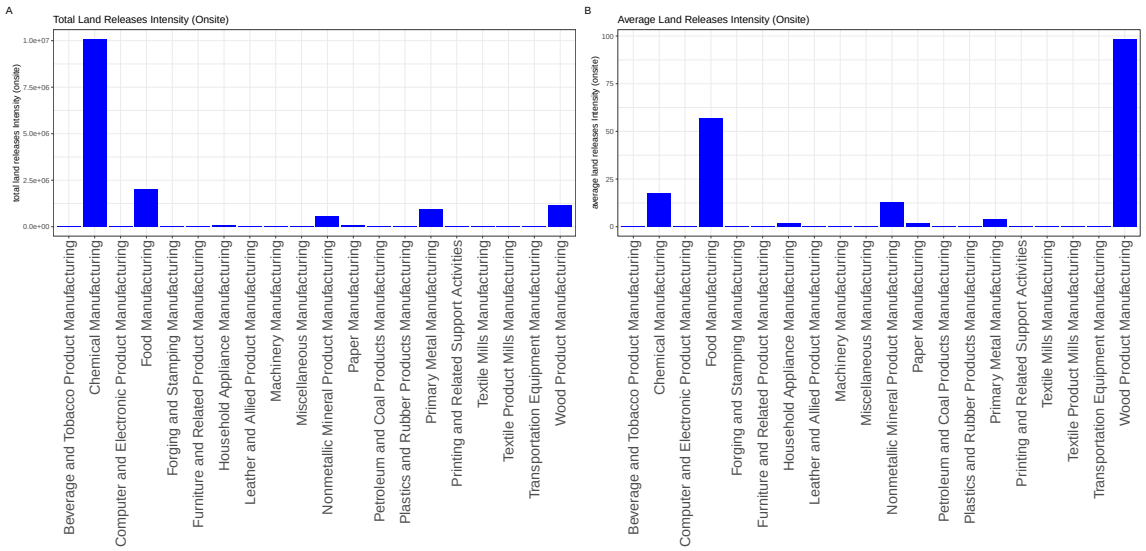



Figure 25: Distribution of Total Onsite Land Releases Intensity across Manufacturing Industries

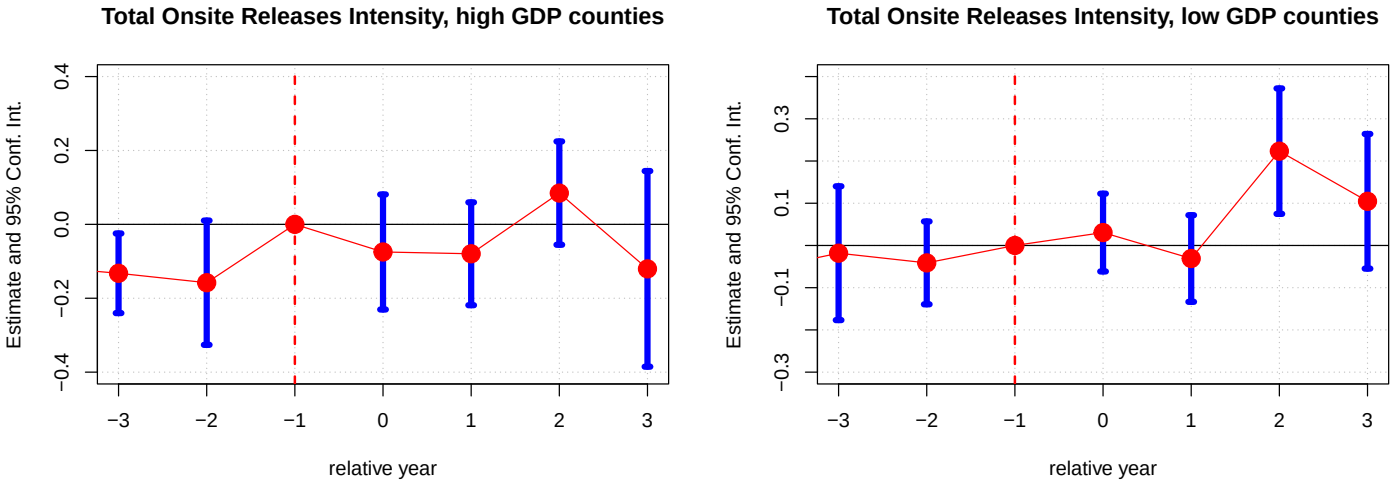



Figure 26: Onsite Total Releases Intensity given Economic Growth Patterns

NOTES: The event study model is given as $P^{gdp}_{f,cp,c,t} = \sum_{e=-3,e\neq-1}^{3} \beta(Treated^e \cdot H)_{f,s,t} + \psi(Treated^e)_{s,t} + \vartheta(Treated \cdot H)_{f,s,t} + \mu(Post \cdot H)_{f,s,t} + \tau Treated_{s,t} + \rho H_{f,s,t} + \alpha Post_t + \sigma X_{v,c,t-1} + \omega F_{f,t} + \lambda_t + \gamma_f + \eta_{c,t} + \theta_{cp,t} + \varepsilon_{f,cp,c,t}$. Where $H_{f,s,t} \in \{1, 0\}$, for high GDP counties. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels.

Table 22: Heterogeneous Characterization ofTotal Onsite Toxic Releases Intensity

| | Profitability, Technology and Competition | | | Types of Toxic Chemicals | | |
|---|---|---|---|---|---|---|
| Toxic release intensity (log) | 1 | 2 | 3 | 4 | 5 | 6 |
| $Treated^e \cdot D$ | -0.046 | -0.179* | -0.025 | 0.011 | 0.067 | -0.028 |
| | (0.089) | (0.093) | (0.067) | (0.096) | (0.096) | (0.103) |
| $Treated^e$ | 0.199*** | 0.077 | 0.067 | 0.101* | 0.068 | 0.142*** |
| | (0.066) | (0.095) | (0.064) | (0.060) | (0.071) | (0.052) |
| cohort 2014 $\cdot D$ | 0.061 | -0.117 | -0.095 | -0.043 | 0.027 | 0.021 |
| | (0.109) | (0.097) | (0.081) | (0.109) | (0.118) | (0.139) |
| cohort 2015 $\cdot D$ | -0.322*** | -0.262** | 0.052 | 0.112 | 0.129 | -0.108 |
| | (0.106) | (0.108) | (0.087) | (0.128) | (0.129) | (0.143) |
| cohort 2017 $\cdot D$ | -0.059 | 0.064 | 0.213 | 0.163 | 0.914*** | -1.160*** |
| | (0.124) | (0.263) | (0.134) | (0.289) | (0.278) | (0.315) |
| controls | Yes | Yes | Yes | Yes | Yes | Yes |
| year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| facility FE | Yes | Yes | Yes | Yes | Yes | Yes |
| toxic chemical $\times$ year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| border-county pair $\times$ year FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 785,762 | 1,107,927 | 1,893,689 | 1,893,689 | 1,893,689 | 1,893,689 |
| $R^2$ | 0.756 | 0.788 | 0.728 | 0.727 | 0.727 | 0.727 |

NOTES: These results are obtained from estimating equation 8. Three-way clustered robust standard errors are reported in parentheses, and clustered at the toxic chemical, industry and state levels. ***, **, and * denote significance levels at the less than 1%, 5% and 10%, respectively. HPLI means high profit and labour-intensive industries. HPCI means high profit and capital-intensive industries. LPLI means low profit and labour-intensive industries. LPCI means low profit and capital-intensive industries. Columns $1-2$ are for HPLI v. HPCI, and LPLI v. LPCI, respectively. Column 3 is for HCI v.LCI. HCI means highly concentrated industries. LCI means low concentrated industries. Column 4 is for carcinogenic v. non-carcinogenic toxic chemicals. Column 5 is for common CAA-HAPs v. uncommon CAA-HAPs toxic chemicals. And Column 6 is for PBTs v. non-PBTs toxic chemicals.

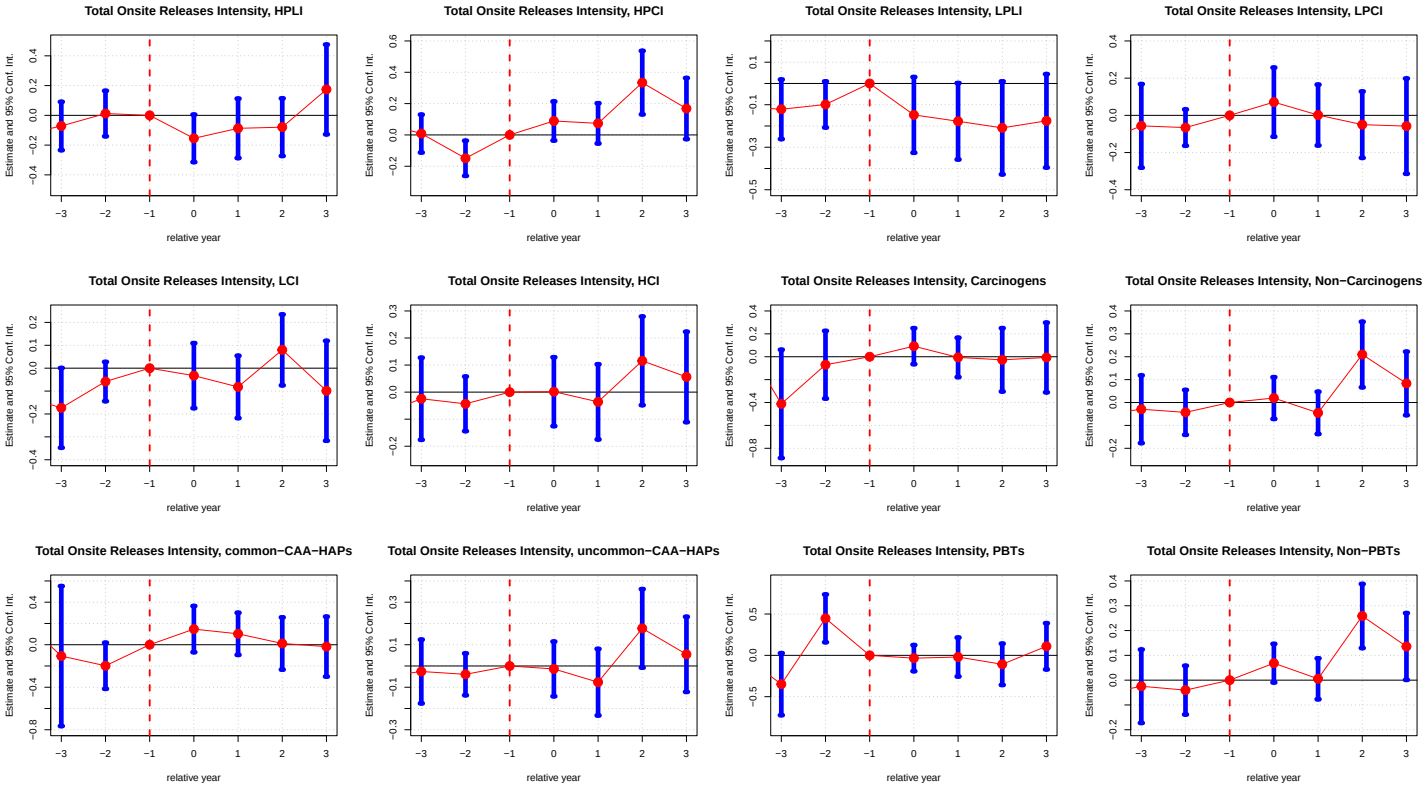



Figure 27: Heterogeneous Characterization of Total Onsite Toxic Releases Intensity

NOTES: These results are obtained from estimating equation 8.

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