

Internal Markets for Liability: Evidence from Medical Monitoring Claims

Abstract

We study how firms respond to increased environmental liability using their internal markets. We exploit the staggered adoption of Medical Monitoring Claims (MMCs) across U.S. states. MMCs allow plaintiffs exposed to hazardous substances to seek compensation for periodic medical examinations, even in the absence of physical injury. Using a difference-in-differences approach, we find that MMC adoption reduces the liable units' toxic emissions by over 2%. The effect is larger for carcinogenic and airborne pollutants, and when chemicals are reclassified from non-carcinogenic to carcinogenic. These effects are driven by single-unit, single-state firms, whereas multi-unit, multi-state firms arbitrage and strategically adjust emissions. Finally, reductions in emissions within multi-unit firms are larger for units in counties with higher levels of civic engagement and for units with greater environmental capability. Our findings show the working of an internal market that facilitates regulatory arbitrage.

Keywords: Medical Monitoring Claims; Toxic Emissions; Multi-unit Business Firms; Firm Scope; Institutional Arbitrage

JEL: G32, G38, Q52

1 Introduction

“This independent panel will study the members of this class to determine whether C-8 exposure has led to increased incidents of disease in this region. If the panel finds that there are probable scientific links to a particular disease, the health of everyone in the class will be monitored for that disease in perpetuity at DuPont’s cost, up to \$235 million.”

—from the class action settlement agreement in
Leach v. E.I. du Pont de Nemours and Co.

Internal markets are an important feature of multi-unit firms. Despite potential agency costs that can reduce some of their benefits (Scharfstein and Stein, 2000; Rajan et al., 2000; Duchin and Sosyura, 2013; Seru, 2014), the internal markets allow firms to reallocate financial, labor, and other resources across units without having to deal with frictions in the external markets (Stein, 1997; Matvos and Seru, 2014; Chauvin et al., 2024). As a result, multi-unit firms are found to possess greater flexibility and resilience under uncertainty than single-unit firms (Almeida et al., 2015; Dickler et al., 2022; Chauvin and Poliquin, 2024). However, such flexibility in reallocation through internal markets can also pose challenges for regulators and policymakers. For example, the Clean Air Act Amendments (CAAA) may become less effective when U.S. multinational firms respond by reallocating assets to their foreign units (Hanna, 2010). The California Cap-and-Trade program may have reduced greenhouse gas emissions from Californian plants but increased emissions from plants owned by the same parent firm located elsewhere (Bartram et al., 2022; Lee and Kaul, 2025).

The benefits of an internal market in reallocation flexibility in response to regulatory pressure should be more salient when (1) the firm has multiple units to facilitate reallocation, (2) the regulatory pressure is fragmented and imposes varying liability and hence reallocation demand across different units within the same firm is greater, (3) there is great heterogeneity in the capacity to manage environmental liability and hence reallocation opportunity across units, (4) firms’ reputation is less sensitive to internal reallocation than to public scrutiny. Therefore, in this paper, we first study how facilities within single- and multi-unit firms differ in their response to fragmented environmental liability. We then examine how facilities within multi-unit firms respond differently according to their environmental capability and their parent firms’ reputations.

Our empirical context is the staggered recognition of Medical Monitoring Claims (MMCs) in the US. Before MMCs, the 1976 Toxic Substances Control Act (TSCA) allows the U.S. Environmental Protection Agency (EPA) to regulate a firm’s chemical releases only after the evidence of harm has been established. In contrast, under tort law, MMCs allow plaintiffs to seek court-ordered medical surveillance after exposure to hazardous substances, at the expense of the firm that released the substances, even in the absence of present injury. Since 1984, 18 states have formally adopted MMCs (Behrens and Appel, 2020). Unlike the Clean Air Act, the Clean Water Act, and the Cap-and-Trade program, MMCs do not directly regulate a firm’s emissions. Instead, MMCs expose firms to contingent liabilities and reputational damage, thereby increasing the potential long-term costs of toxic emissions. The null hypothesis is that firms can choose not to reduce pollution either because they underestimate the company’s exposure to liability or because the benefits of polluting outweigh the medical monitoring costs (Shapira and Zingales, 2025). We aim to investigate whether potential liability causes companies to internalize long-term social consequences in their short-term actions (Bénabou and Tirole, 2010).

We source data from the EPA’s Toxics Release Inventory (TRI), which tracks most toxic chemicals that pose risks to human health and the environment. Analyzing unit-level emissions in relation to the staggered adoption of MMCs, we first find that units in MMC-adopting states reduce toxic emissions significantly more than those in non-adopting states. The reductions are particularly pronounced for substances that pose severe health risks to humans or are readily absorbed by humans, such as pollutants with carcinogenic effects and airborne emissions.

We then examine how units’ emission reductions vary by their parent firms’ organizational scope. In our sample, more than three-quarters of firms have at least two reporting units. We find a 4.5% reduction in emissions relative to the sample mean for single-unit firms, compared with a substantially smaller reduction (and statistically insignificant) of 1% for multi-unit ones. Similarly, single-state firms reduce emissions more than multi-state firms. To uncover evidence of regulatory arbitrage through internal markets by multi-unit firms, we examine whether individual units operate in an arm’s-length or arm-in-arm fashion within a firm. We find that, among single-state multi-unit firms, units with greater past emissions reduce more than their sibling units, suggesting that units facing greater liability exert greater effort. In addition, for multi-state firms, units in non-adopting states increase emissions after their sibling units’ states have adopted

MMCs. Together, these findings suggest that multi-unit firms strategically reallocate pollution to places with lower environmental liability.

Finally, we explore how emission reductions vary with firms’ external pressure and internal capabilities. We find that the emission reduction following MMCs adoption is significantly larger for units of multi-unit firms located in counties with stronger social activism, consistent with prior work on institutional arbitrage (Hiatt et al., 2015; Lee and Kaul, 2025; Hou and Poliquin, 2023). In addition, emission reductions are more pronounced among environmentally capable units of multi-unit firms (Chava, 2014).

Taken together, our findings highlight that the internal market enables firms to arbitrage emissions across their units in response to changes in environmental liability. Our paper is closely related to the growing literature on how firm characteristics, such as financing constraints, stakeholder pressure, and ownership structure, shape their responses to changing environmental landscapes. Bartram et al. (2022) find that financially constrained firms have to shift emissions across plants to avoid California’s cap-and-trade regulation. Chen (2025) shows that financially weaker firms reduce emissions more after the 2002 Brownfield Act relieved buyers of contaminated sites from cleanup liabilities. Xu and Kim (2022) shows that financing constraints exacerbate toxic pollution as waste management is costly, especially under weak regulatory monitoring. Duchin et al. (2025) find that firms divest pollutive assets in response to environmental pressures. In particular, this paper relates to studies on how organizational form influences firms’ response to environmental liability. Using a Supreme Court decision that limited parent liability from subsidiaries, Akey and Appel (2021) find that subsidiaries emit more when their parent firms are protected from the subsidiaries’ liability for environmental damages. Bellon (2025) shows that private equity ownership reduces firm pollution in response to heightened litigation and regulatory risks. And Dasgupta et al. (2023) show that plants monitored by socially responsible mutual funds cut more toxic emissions in response to EPA enforcement on peer firms. Our findings provide new evidence on the role of the multi-unit organizational form in strategic regulatory avoidance and risk shifting.

Our paper also contributes to a large literature on firms’ arbitrage across institutional contexts, where policies targeting specific geographic areas create opportunities for arbitrage in compliance (Greenstone, 2002; Nordhaus and Yang, 1996; Bushnell et al., 2017; Fowle et al., 2016; Colmer et al., 2025; Bartram et al., 2022; Bellon, 2025). In particular, it relates to the literature on the “Pollution Haven Hypothesis”, which has

explored how multinational corporations engage in institutional arbitrage by locating production in countries with relatively lax environmental standards (Aragón-Correa et al., 2016; Li and Zhou, 2017; Berry et al., 2021; Hanna, 2010; Dowell et al., 2000). We complement this literature by distinguishing between single- and multi-unit firms in their arbitrage capacity. Our analysis at the unit level extends prior work on environmental strategy at the firm level (Li, 2025; Li and Flammer, 2025).

Finally, our study adds to the extensive literature on the costs and benefits of internal markets.¹ Findings on the “bright side” of internal markets emphasize their information advantage and flexibility in capital allocation (Stein, 1997). This advantage is more available for multi-unit firms (Maksimovic and Phillips, 2002; Helfat and Eisenhardt, 2004; Sakhartov and Folta, 2014), especially in times of financial frictions and industry distress (Matvos and Seru, 2014; Almeida et al., 2015; Kuppuswamy and Villalonga, 2016; Matvos et al., 2018). Findings on the “dark side” indicate that cross-subsidization and corporate socialism have inefficient consequences for capital allocation (Scharfstein and Stein, 2000; Rajan et al., 2000). Our paper contributes to this debate by uncovering a “gray side” in regulatory arbitrage.

This paper proceeds as follows. Section 2 gives an overview of the institutional background. In Section 3, we provide detailed information on data collection and sample construction. Section 4 discusses our identification strategy and the empirical results of our interest. Section 5 concludes.

2 Institutional Background

Medical Monitoring Claims (MMCs) allow plaintiffs exposed to hazardous substances to recover the costs of medical surveillance before any diagnosable injury occurs (Geistfeld, 2024). The rationale is that early detection can reduce the long-term cost of the illness. However, U.S. courts are divided on whether a present injury is necessary to support such claims. In some jurisdictions, plaintiffs may recover medical monitoring expenses solely on the basis of an increased risk of harm from toxic exposure. In others, the absence of a diagnosable injury renders such claims legally void. This split reflects a deeper tension in tort law—between precautionary compensation that internalizes ex ante environmental risk and traditional legal standards that require ex post demonstrable

¹A more complete summary of the extensive literature on conglomerates is available in Maksimovic and Phillips (2007).

harm.

The District of Columbia (DC) was among the first jurisdictions to recognize MMC in the absence of present injury. In the 1984 decision in *Friends for All Children v. Lockheed Aircraft Corp.*, the U.S. Court of Appeals for the District of Columbia held that survivors of a toxic exposure incident were entitled to compensation for ongoing medical surveillance as they faced long-term health risks. In contrast, some states refused to recognize MMCs without proof of a present injury. For example, in *Hinton v. Monsanto*, the plaintiff, Travis Hinton, alleged that the defendant, Monsanto’s chemical plant in Anniston, Alabama, had contaminated the environment by exposing residents to toxic polychlorinated biphenyls (PCBs). Hinton claimed that although he suffered no physical injuries, the defendant needed to compensate him for the medical monitoring expenses due to his exposure to toxic substances. However, the Supreme Court of Alabama in 2001 refused to recognize a cause of action for medical monitoring. Many other states remain unsettled, with courts undecided or awaiting legislative direction.

By 2022, 18 jurisdictions have passed medical monitoring claims. Among them, thirteen states and the District of Columbia explicitly ratified the resolution. In addition, four states are considered by legal scholars and practitioners to lean toward recognition, despite the absence of definitive precedents (Behrens and Appel, 2020). Colorado is a case in point. In *Cook v. Rockwell International Corp.*, landowners near the Rocky Flats Nuclear Weapons Plant sought compensation for losses caused by a leak from this nuclear power plant. Although the Colorado Supreme Court has not taken a position on MMC, several district court decisions in Colorado² have concluded that the Court would recognize MMC as a cause of action (Behrens and Appel, 2020).

The remaining 33 states either reject medical monitoring outright or lack sufficient precedent to support its recognition. In the absence of clear, repeated, or influential rulings, we classify these as non-adopting states. Based on a comprehensive review of case law and literature, we summarize the status of medical monitoring across all 50 states and the District of Columbia. A map of state-by-state MMC adoption is provided in Figure 1. A more detailed summary of each state’s stance on medical monitoring, whether it is adopted or not, and the year of adoption is summarized in Table 1³.

When we examine the factors underlying the adoption of MMCs, we find little evidence that important observable state-level characteristics predict whether or when

²*Cook v. Rockwell Int’l Corp.*, 755 F. Supp. 1468, 1477 (D. Colo. 1991); *Bell v. 3M Co.*, 344 F. Supp.3d 1207, 1224 (D. Colo. 2018).

³Additional details on the related cases are provided in Appendix Table A1.

states decide to recognize MMCs. Panel A of Table A3 presents the results using various judicial and regulatory factors. The results show that state-level exposure to federal regulation, the volume of state-specific regulation, or judicial intensity does not predict MMC adoption. Moreover, socio-economic factors such as GDP growth, unemployment, population, and pollution exhibit no predictive power. These results suggest that MMC adoption events are largely unanticipated and do not correlate with other economic and legal factors.

Although fewer than half of the states have recognized MMCs, we find that MMC adoption leads to improvements in local public health. Table A4 in the Appendix presents evidence on health expenditures and cancer incidence, based on data from the CDC Wonder database. Specifically, using data from the Centers for Medicare & Medicaid Services (CMS), we show that MMC adoption is followed by a decline in total personal health-care expenditures at the state level after controlling for GDP growth, unemployment, income, and population. More importantly, we find that states that recognize MMCs exhibit lower long-run cancer incidence rates among residents. Together, these findings suggest that MMCs reduce exposure to carcinogens and improve real public health outcomes.

3 Data and Sample

Our baseline sample comprises all US-based units covered by the Environmental Protection Agency’s (EPA) Toxics Release Inventory (TRI) database from 1987 to 2022. The TRI database has become one of the most widely used sources for tracking unit-level environmental performance over time (Hamilton, 1995; Konar and Cohen, 1997; Levine et al., 2018; Banerjee et al., 2014; Currie et al., 2015; Shapiro and Walker, 2018; Xu and Kim, 2022). Since 1987, the TRI has collected annual, chemical-specific emissions data from units that exceed minimum thresholds related to employment, industry classification, and chemical usage.⁴ Furthermore, for each reportable chemical, units must disclose the emissions released to air, water, and land. The TRI database also includes each unit’s parent company identifier via the Dun & Bradstreet DUNS number.

We focus on TRI data for three main reasons. First, it provides comprehensive, long-

⁴Under current reporting rules, units are required to report if they employ at least ten full-time workers and handle any of approximately 600 listed toxic chemicals. Reporting is generally triggered if a unit manufactures or processes more than 25,000 pounds of a chemical annually or uses more than 10,000 pounds.

term coverage of industrial pollution at the unit level, enabling consistent comparisons over time and across regions. Second, emissions are reported at the chemical level, allowing for granular analysis that accounts for variation in pollutant toxicity across substances and environmental media. Third, although TRI data are self-reported, they are subject to EPA audits. As a result, misreporting is generally rare (Brehm and Hamilton, 1996; de Marchi and Hamilton, 2006; Bui and Mayer, 2003)⁵. Moreover, units may face civil or criminal penalties for misreporting (Xu and Kim, 2022; Greenstone, 2003), thereby reducing incentives to underreport emissions.

We obtain pollutant-level toxicity weights from the EPA’s Risk-Screening Environmental Indicators (RSEI) model. These weights reflect the relative human health risks associated with long-term chemical exposure and are based on the most sensitive observed effect for each exposure pathway (oral or inhalation). In particular, RSEI accounts for both cancer and non-cancer endpoints, including reproductive, developmental, and respiratory effects. Following Toffel and Marshall (2004), we match RSEI toxicity weights to TRI emissions using Chemical Abstract Services (CAS) numbers and construct toxicity-weighted emission measures for both carcinogenic and non-carcinogenic risks. This approach allows us to quantify whether and to what extent TRI-listed substances pose health risks.

We aggregate RSEI toxicity-weighted emissions from pollutant level to unit level. Note that as RSEI assigns separate cancer and non-cancer toxicity weights to each chemical and retains the higher value when constructing the overall toxicity index, the resulting *Toxic Emissions* is not the arithmetic sum of *Toxic_Carcinogen* and *Toxic_nonCarcinogen*.

Our sample is restricted to units with a valid parent-company DUNS number⁶ and located in the 50 U.S. states or the District of Columbia. To ensure sufficient coverage for panel analyses, we further require that each unit report emissions for at least two consecutive years. Our final sample consists of 500,407 unit-year observations, corresponding to 36,478 unique units owned by 10,588 firms. Most units are from chemical manufacturing (17.5%), fabricated metal products (11.4%), food manufacturing (9.3%), and nonmetallic mineral products (7.3%). Table 2 presents summary statistics for the variables of interest.

⁵For example, Brehm and Hamilton (1996) and de Marchi and Hamilton (2006) find that reporting errors are concentrated among units with low emissions, likely reflecting unintentional mistakes rather than strategic misrepresentation.

⁶In robustness tests, we also check the validity of our baseline findings for all TRI units, including those without a valid parent-company DUNS number.

[Insert Table 2 About Here]

4 Empirical Analysis

4.1 MMC, Judicial Actions and Toxic Releases

Before turning to our main analysis, we present initial evidence on the effects of MMC adoption. Firstly, we examine the differences in civil judicial enforcement activities between MMC-adopting and MMC-exempt states. Panels A and B of Figure 2 reveal that MMC-adopting states are more active in pursuing judicial action against units' environmental misconduct. In particular, MMC-adopting states have a larger number of civil judicial actions and greater total monetary penalties associated with those actions over our sample period. This pattern validates that MMCs increase businesses' legal liability for toxic emissions. Secondly, Panel C indicates that average onsite toxic releases are significantly lower in MMC states. These cross-sectional comparisons suggest that MMC adoption is associated with stronger judicial enforcement and lower emissions. In the next section, we proceed to identify the causal effect of MMCs on toxic emissions.

[Insert Figure 2 About Here]

4.2 Identification Strategy

We exploit the staggered adoption of MMC across states with a difference-in-differences (DID) framework to examine its impact on toxic emissions. As discussed above, the timing of MMC implementation was largely unanticipated, allowing us to treat it as an exogenous shock. Specifically, we estimate the following DID model:

$$\text{Log}(Toxics)_{ifst} = \beta_0 + \beta_1 MMC_{st} + \beta_2 Ctrl_{ft} + \beta_3 Ctrl_{st} + \pi_t + \pi_i + \varepsilon_{ifst} \quad (1)$$

In Equation (1), i indexes unit, f indexes parent firm, s indexes state of location, and t indexes years. The unit of observation is a unit-year.

In this DID specification, the dependent variable $\text{Log}(Toxics)$ denotes the natural logarithm of toxicity-weighted RSEI emissions at the unit level. The key explanatory variable is an indicator variable MMC_{st} , which equals one when state s had adopted MMC by year t , and zero otherwise. The specification includes two sets of controls.

Firm-level controls, $Ctrl_{ft}$, include the number of states in which the parent firm operates TRI-reporting units and the number of units owned by the same parent firm within the same state. State-level controls, $Ctrl_{st}$, include annual GDP growth, unemployment rate, personal income, and total population. These variables help to control for some broader socioeconomic factors that may affect toxic emissions.

To address concerns about omitted variables, our baseline specification in Equation (1) includes year fixed effects (π_t) and unit fixed effects (π_i). Given that MMC adoption occurs at the state level, we cluster standard errors by state throughout the analysis. This clustering accounts for potential autocorrelation within states over time and cross-sectional dependence across units located within the same state (Bertrand et al., 2004).

[Insert Table 3 About Here]

We present our baseline results in Table 3. Column (1) reports the results when we include only unit- and year-fixed effects. The coefficient estimate of the MMC indicator is -0.237 and statistically significant at the 5% level. This negative estimate indicates that units located in MMC-adopting states reduce more toxic emissions than those in non-adopting states, after controlling for time-invariant unit characteristics and nationwide time-varying factors. We then add time-varying firm-level controls, including the number of states in which a firm operates TRI-reporting units and the number of units within each state. According to the results in Column (2), the coefficient on MMC remains negative and statistically significant at the 5% level, with a point estimate of -0.231 . In Column (3), we augment the regression with state-level economic controls, including GDP growth, unemployment, per capita income, and population, to account for local economic conditions that may confound our findings. The estimate on MMC barely changes, dropping slightly to -0.213 . The reduction in toxic emissions is also economically meaningful, as the point estimate corresponds to a 2% decline relative to the sample mean.

4.2.1 Carcinogenic Risk and Media of Emission

To further understand what drives the observed decline in toxic emissions, we focus our attention on two key aspects of emissions, that is, pollutants with carcinogenic risks and the medium of emissions.

[Insert Table 4 About Here]

Panel A in Table 4 decomposes emissions-induced health risks by carcinogenic and non-carcinogenic risks. The estimated coefficient on MMC is -0.335 for carcinogenic emissions in Column (1), significant at the 1% level. In contrast, the effect on non-carcinogenic emissions is much smaller in Column (2), with an estimate of -0.154 and statistically significant only at the 10% level. Such contrasting patterns suggest that firms respond more proactively to reduce emissions that pose substantial cancer risks following MMC adoption.

Panel B in Table 4 turns to the channels through which emissions are transmitted. As noted by Brunekreef and Holgate (2002) and Landrigan (2017), exposure to airborne pollutants is closely associated with increased mortality and hospital admissions due to respiratory and cardiovascular diseases. These effects have been documented in both short-term studies that link day-to-day variations in air pollution to health outcomes and long-term cohort studies that follow exposed populations over time. Consistent with this evidence, we find that the emission reduction is mostly driven by reductions in air emissions, with an MMC coefficient of -0.194 and significant at the 5% level in Column (1). In contrast, the coefficients on emissions through water, land, and other media are negative but statistically insignificant. These findings are consistent with the conjecture that airborne pollutants are more sensitive to MMCs because they are more likely to affect large populations and are easier to trace.

In sum, these findings imply that firms are selectively reducing certain forms of toxic emissions, rather than curbing emissions across all categories, consistent with Gibson (2019) on regulation-induced heterogeneous responses across media.

4.2.2 Reclassification of Carcinogens

We then use variations caused by an exogenous change to pollutant reporting to further test the carcinogen channel. In particular, we investigate whether the Reclassification of Carcinogens (RoC) by the National Toxicology Program (NTP) changes firms' responses to MMC adoption. The RoC periodically updates its list of recognized carcinogens based on the latest scientific evidence. These updates not only carry regulatory implications but also heighten public awareness and concern regarding exposure to newly identified carcinogens (van Binsbergen et al., 2025). Consequently, units producing these chemicals face intensified scrutiny from households, local communities, and other stakeholders, amplifying both reputational and operational pressures to reduce emissions. This setting provides a unique opportunity to assess the effectiveness of MMC for units' pollution

activities.

We use an event-study framework to examine this question and present the results in Table 5. Following Gormley and Matsa (2011) and van Binsbergen et al. (2025), we classify treated units as those producing chemicals newly identified as carcinogenic under the NTP’s RoC. Event years are defined as the years following the initial classification. We construct a dummy variable, *RoC*, equal to one for treated units in these event years, and zero otherwise. We then re-estimate the baseline specification from Column (3) of Table 3, interacting MMC adoption with *RoC* to examine whether emission reductions are amplified for units affected by the reclassification.

[Insert Table 5 About Here]

The results reveal that MMC-induced reductions in toxic emissions are markedly larger for RoC-affected units. In particular, reductions in carcinogenic emissions are both statistically robust and economically meaningful, whereas the corresponding effects on non-carcinogenic emissions remain modest. Quantitatively, the estimated reduction in carcinogenic emissions for RoC-treated units amounts to roughly 28% relative to the sample mean, highlighting the substantial economic significance of this effect. These findings suggest that updated regulatory classifications can serve as a powerful trigger, enhancing firms’ responsiveness to MMC-induced environmental liability.

4.3 The Role of Organizational Scope

The above analysis highlights firms’ choice to reduce carcinogenic and airborne emissions, suggesting that they respond strategically to heightened environmental liability under MMCs. We next investigate how a firm’s organizational scope shapes the extent to which it internalizes environmental liability. As environmental policies typically target specific geographic areas, they create opportunities for compliance arbitrage across regions (Greenstone, 2002; Colmer et al., 2025; Chen et al., 2025). In this regard, firms’ organizational scope can play an important role in shaping their environmental conduct. In particular, single-unit firms, whose operations are concentrated in a single location, may face more localized reputational, regulatory, and legal burdens than multi-unit firms with a broader footprint. Similarly, among multi-unit firms, those confined to a single state are more constrained by state-specific legal risk than those operating across multiple states. In this section, we examine how firms’ organizational scopes (single-unit vs. multi-unit and single-state vs. multi-state) affect their strategic responses to MMCs.

[Insert Table 6 About Here]

Panel A of Table 6 compares the emission responses of single-unit and multi-unit firms. We begin by presenting subsample regression results for single-unit and multi-unit firms. Column (1) shows that MMC adoptions lead to a significantly large reduction in toxic emissions among single-unit firms, with a coefficient of -0.478 (statistically at 1% level). This effect is economically large, equivalent to a 4.5% decline relative to the sample mean. By contrast, Column (2) reveals that pollution reductions appear to be modest among multi-unit firms, with a statistically insignificant estimate on MMC of -0.114 . Column (3) estimates a different specification that includes an interaction term between MMC and a multi-unit indicator variable. The interaction coefficient is 0.425 and statistically significant at the 1% level, indicating that single-unit firms reduce significantly more emissions in response to MMC adoptions than multi-unit firms.

We then further decompose multi-unit firms into those operating within a single state and those operating across multiple states. Column (1) in Panel B shows that single-state multi-unit firms exhibit a statistically significant large decline in emissions with a coefficient estimate of -1.019 . In contrast, there is no detectable reduction in emissions among multi-state, multi-unit firms, as shown in Column (2). We confirm this difference using a specification with an interaction term in Column (3). Specifically, the estimate of the interaction term is 0.570 and significant at the 5% level, suggesting that MMC-induced pollution reductions are concentrated among single-state multi-unit firms.

In Panel C, we compare all single-state firms, including both single- and multi-unit firms, with firms operating in multiple states. The pattern remains consistent with the preceding findings: single-state firms reduce emissions significantly more with a coefficient of -0.575 and statistically significant at the 1% level, while multi-state firms exhibit no discernible reduction in pollution. The interaction term estimate of 0.494 (significant at the 1% level) suggests that multi-state firms are less responsive to MMCs relative to their single-state counterparts.

4.4 Within-Firm Emission Adjustment

The evidence thus far suggests that single-unit firms cut toxic emissions sharply in response to MMC adoption relative to their multi-unit peers. This difference underscores the need to further examine how multi-unit firms leverage their organizational scope to navigate local environmental liability.

In this section, we examine in detail how multi-unit firms adjust their emissions. The first exercise focuses on intrastate adjustment by examining whether emission reductions within a firm are concentrated in its dirtiest units, i.e., those most exposed to environmental liability under MMCs. The second exercise turns to cross-state reallocation, exploring whether multi-state firms shift pollution toward units located in MMC-exempt states.

4.4.1 Intra-state Adjustment within Firms

Table 7 provides evidence of whether multi-unit firms disproportionately cut emissions at their dirtiest in-state units. We classify units based on their within-firm emissions ranking and construct an indicator for those in the top 40th percentile. We then interact this indicator with MMC adoption to test whether pollution reductions are more pronounced among these relatively dirtier units.

[Insert Table 7 About Here]

Column (1) in Table 7 presents results for the full sample of multi-unit firms. The interaction term for the dirtiest units is negative but statistically insignificant, providing only modest evidence of targeted readjustment. Column (2) restricts the sample to single-state multi-unit firms and reveals a significant effect: The interaction term estimate is -0.680 and statistically significant at the 1% level. This finding indicates that emission cuts are concentrated in dirty in-state units for single-state multi-unit firms. In contrast, Column (3) shows no such pattern among multi-state firms, where the interaction estimate is modestly negative and statistically indistinguishable from zero. These findings suggest that intrastate reallocation is an important adjustment strategy at the firm level, especially for multi-unit, single-state firms.

4.4.2 Cross-state Adjustment within Multi-state Firms

Building on the evidence that single-state multi-unit firms engage in strategic intrastate reallocation, we next examine whether multi-state firms exploit their broader geographic footprint to engage in cross-state institutional arbitrage. In particular, multi-state firms may reallocate pollution across state borders in response to differences in regulatory stringency. To this end, we examine whether units located in non-MMC states alter emissions when their parent firms also operate other units in MMC-adopting states. In particular, we construct two firm-level measures of MMC exposure: $FMMC1$, an

indicator that equals one if the firm operates any units in MMC-adopting states in the past two years, and $FMMC2$, defined as the share of the firm’s units located in MMC-adopting states.

[Insert Table 8 About Here]

Both specifications in Table 8 provide robust evidence of interstate emission arbitrage. Column (1) shows that units in non-MMC states increase emissions when their parent firms’ other units are exposed to MMCs elsewhere: the coefficient on $FMMC1$ is 0.208 and statistically significant at the 1% level. Column (2) confirms that the emissions increase with the degree of firm-level MMC exposure: the coefficient on $FMMC2$ is 1.110 and significant at the 1% level.

Recalling that units of multi-state firms in MMC-adopting states show small, statistically insignificant emission reductions, the documented emission increases in sister units in non-adopting states pose a puzzle. To reconcile this, we estimate firm-year regressions of total toxic emissions for multi-state firms. As reported in Table A2, the net effect on total firm-level emissions is not statistically significant, indicating that increases at unaffected units largely offset modest reductions at affected ones. These findings suggest that MMC primarily induces a spatial reallocation of emissions across states rather than a net increase in firm-wide pollution.

Taken together, the evidence points to a strategic readjustment of toxic emissions within the firm. When facing localized environmental liability, firms do not necessarily cut pollution; they relocate it. Such cross-state arbitrage underscores the “gray side” of multiunit firms, thereby weakening the effectiveness of region-specific regulations.

4.5 Cross-sectional Analysis

To further explore the underlying mechanisms, we examine how multi-unit firms’ responses to MMC adoption vary along two dimensions: internal capabilities and external forces.

4.5.1 Internal Capability

In this subsection, we dig into the internal factors that influence multi-unit firms’ responses to MMC adoption.

4.5.1.1 Financial Constraint

We first investigate whether firms’ financial constraints affect their ability to respond to environmental liabilities induced by MMC adoption. Financially constrained firms have limited liquidity and face high external financing costs, which restrict their capacity to make capital-intensive adjustments, such as upgrading pollution abatement technologies, redesigning production processes, or investing in cleaner inputs. In contrast, unconstrained firms can reallocate financial resources internally or access credit markets more easily to cover medical monitoring expenses. Hence, if environmental compliance imposes high adjustment costs, one would expect financially constrained firms to exhibit weaker emission responses following the adoption of MMC.

In Table 9, we begin by validating that the previously-documented weaker MMC-induced emission reductions observed among multi-unit firms in the baseline results also hold within the listed-firm sample, where we can explicitly characterize firms’ financial constraints due to data availability. In Column (1), we re-estimate the specification reported in Column (3) of Table 6 using the matched sample of publicly listed firms. Consistent with the full sample evidence, multi-unit firms among listed companies also exhibit significantly smaller reductions in toxic emissions following MMC adoption.

[Insert Table 9 About Here]

Next, to address potential concerns that these results may be confounded by contemporaneous changes at the listed-firm level, such as variation in investment cycles or growth opportunities, we augment the baseline specification in Column (2) with a rich set of time-varying firm-level controls.⁷ By conditioning on these observable firm-level characteristics, this specification helps isolate within-firm differences in units’ responses that are not mechanically driven by common firm-level dynamics. The robustness of our core finding under this specification confirms that the weaker response among multi-unit firms is not driven by time-varying firm-level factors.

After establishing that the main pattern holds in the listed-firm universe, Column (3) turns to examine how financial constraints shape the heterogeneity in MMC-induced responses. In the same spirit as Bartram et al. (2022), we construct a composite indicator of financial constraints by combining four widely used proxies, including the KZ index (Kaplan and Zingales, 1997), the SA index (Hadlock and Pierce, 2010), the

⁷These controls include firm size, leverage, profitability, cash holding, sales growth, asset tangibility, operating cash flow, and acquisition expense.

WW index (Whited and Wu, 2006), and firm size. For each proxy, a firm is classified as financially constrained if its index value lies above the sample median (or below the median for firm size). The composite indicator defines a firm as constrained ($FC = 1$) if the majority of these four proxies identify it as financially constrained; otherwise, it is categorized as unconstrained ($FC = 0$).

The results in Column (3) reveal that pollution reductions among multi-unit firms following MMC adoption are significantly smaller for units belonging to financially constrained ones. This pattern indicates that financial constraints further discourage multi-unit firms from cutting toxic emissions, limiting their ability to internalize environmental liabilities and comply effectively with regulatory mandates. Interestingly, the $FC \times MMC$ coefficient for single-unit firms is negative (although statistically insignificant), reflecting that financially constrained single-unit firms likely reduce emissions more than their unconstrained counterparts. This contrast highlights that financial constraints shape how emission responses differ across organizational scopes, amplifying the divergence between multi-unit and single-unit firms.

Taken together, these findings underscore that the effects of financial constraints on environmental compliance are nuanced and, in particular, contingent on firms' organizational footprint. Our results complement Bartram et al. (2022), which shows that financially constrained firms reallocate emissions and output from regulated states to less stringent regions.

4.5.1.2 Environmental Capability

We proceed to examine the role of unit-level environmental capabilities in shaping multi-unit firms' responses to MMC adoption. While organizational scopes and financial resources influence a firm's capacity to adjust to changes in environmental liability, the effectiveness of such adjustments critically depends on the capabilities embedded at the unit level. Units with effective abatement technologies or environmental management systems can readily adapt processes, substitute inputs, and implement cleaner production methods to comply with regulatory standards (Chin et al., 2013; Berchicci et al., 2012). Consequently, multi-unit firms with stronger internal environmental capabilities are expected to meet environmental requirements more efficiently and thus exhibit a stronger pollution reduction.

To test this hypothesis, we use data from the EPA's Pollution Prevention P2 database to construct unit-level measures of environmental capability. Specifically, we

construct indicators for whether a unit has adopted processes or non-process abatement technologies in the past five years. The results in Table 10 suggest that pollution reductions among multi-unit firms following MMC adoption are significantly larger among units with greater process and non-process abatement ability.

[Insert Table 10 About Here]

To sum up, these findings demonstrate that internal capabilities play a critical role in shaping multi-unit firms' environmental compliance, with stronger capabilities enabling units to respond more effectively to regulatory mandates. The heterogeneity in unit-level responses further highlights that policy outcomes are not uniform across firms: even within the same multi-unit firm, differences in technological sophistication determine the magnitude of emission reductions. In particular, this underscores the interplay between organizational scope and internal capabilities; that is, while multi-unit firms possess structural advantages that could facilitate regulatory arbitrage, their ability and incentives to leverage these advantages depend on the technological capacity at individual units.

4.5.2 External Factors

In this subsection, we examine the external factors that moderate multi-unit firms' responses to MMC adoption.

4.5.2.1 External Social Activism

We begin by exploring whether local social activism shapes how multi-unit firms respond to MMC adoption. While MMCs impose state-level legal environmental liability, firms' actual compliance behavior is also influenced by the social and institutional environment in which their units operate. Social activists can raise reputational costs and operational risks through public campaigns, protests, or litigation threats (Brehm and Hamilton, 1996; Eesley and Lenox, 2006; King, 2008), creating an additional layer of external pressure beyond formal regulation. We hypothesize that units located in communities with limited civic engagement or greater tolerance for regulatory noncompliance may face weaker incentives to reduce pollution, thereby contributing to regional disparities in corporate environmental performance (Mohai et al., 2009).

To empirically test this hypothesis, we use two proxies to capture local social activism. First, we consider the county-level share of votes cast for the Democratic presidential

candidate from 2000 to 2022, drawing on evidence that stakeholder engagement in social and environmental issues is generally stronger in Democrat-leaning counties (Hou and Poliquin, 2023). Second, we measure the presence of environmental non-governmental organizations (NGOs) headquartered in a county, which can monitor local emissions and impose informal reputational or operational costs on noncompliant units (Hiatt et al., 2015; Luo et al., 2018; Lee and Kaul, 2025). NGO data are sourced from the IRS Exempt Organizations Business Master File, while election data come from the MIT Election Lab.

[Insert Table 11 About Here]

Table 11 reports the results where these proxies are interacted with MMC adoption to present the heterogeneity in multi-unit firm responses. Across both proxies, the interaction term coefficients are negative and statistically significant, indicating that MMC-induced emission reductions are larger among multi-unit firms in counties with stronger civic engagement. These findings suggest that social activism acts as an amplifier of regulatory enforcement: beyond the legal liability imposed by MMCs, external pressures from local communities and organized stakeholders can strengthen multi-unit firms’ incentives to comply. In other words, even firms with structural advantages to arbitrage regulatory obligations are more constrained in their ability to shirk when operating in socially active environments. These results highlight the interplay between formal regulation and community-level enforcement mechanisms.

4.5.2.2 Campaign Finance Rules

We next assess whether multi-unit firms’ responses to MMC adoption vary across the campaign finance environment. Contributions can shape emissions through two opposing channels. On one hand, they may enhance the returns to compliance, for example, via subsidies, tax incentives, or favorable regulations, encouraging firms to reduce emissions. On the other hand, firms could use contributions to lobby for laxer rules or support candidates favoring lenient regulation, potentially dampening compliance (Bombardini and Trebbi, 2020; Bisetti et al., 2025). The net effect is ambiguous, leaving the balance between these channels to be determined empirically.

[Insert Table 12 About Here]

Following Ash et al. (2025), we use the Book of States to identify whether states prohibit contributions from organizations, including corporations and labor unions.

Table 12 presents the results. Consistent with our hypothesis, MMC-induced emission reductions among multi-unit firms are significantly smaller in states that prohibit corporate political contributions. This pattern indicates that the ability to shape the political environment reinforces compliance: firms respond not only to regulatory mandates but also strategically engage with the institutional context to amplify the returns to compliance. In other words, the environmental behavior of multi-unit firms reflects an interplay between formal rules and the broader governance landscape.

4.6 Additional Results

4.6.1 Dynamic Estimation Testing Parallel Trends

A key threat to our identification strategy is the possibility that our benchmark estimates reflect pre-existing differences between treated and control groups prior to the adoption of MMCs. To address this concern and test the parallel trends assumption underlying the difference-in-differences (DID) framework, we follow the event-study approach outlined by Bertrand and Mullainathan (2003) and Roberts and Whited (2012). Specifically, we replace the baseline treatment indicator MMC with a series of leads and lags that capture the dynamic effects of MMC adoption, spanning five years before and more than six years after implementation. If pre-treatment differences were driving the results, we would expect to see statistically significant coefficients on the pre-treatment indicators.

[Insert Figure 3 About Here]

The results of our dynamic estimation, shown in Figure 3 suggest that pre-shock coefficients are small and statistically insignificant. In contrast, post-shock coefficients are consistently negative and statistically significant across most specifications. In concert, the evidence in Figure 3 strengthens the credibility of our results and mitigates concerns about endogeneity in our baseline findings reported in Table 3.

[Insert Figure 4 About Here]

To address recent critiques of staggered difference-in-differences estimators (Cengiz et al., 2019; Goodman-Bacon, 2021; Sun and Abraham, 2021; de Chaisemartin and D’Haultfoe uille, 2020; Wing et al., 2024), we re-estimate our dynamic specifications using a stacked difference-in-differences design that aligns treated and control units relative to their adoption timing. Moreover, following Wing et al. (2024), we apply

the proposed weighting scheme to correct for potential biases arising from fixed-effects implementations of stacked estimators and to ensure identification of the target aggregate causal effect across treatment cohorts. The resulting stacked DID estimates, reported in Figure 4, exhibit a dynamic pattern similar to Figure 3. This additional evidence reinforces the robustness of our findings and further mitigates concerns regarding endogeneity in our baseline results.

4.6.2 Robustness Checks

We conduct a battery of robustness checks to assess the robustness of our main findings, as summarized in Table 13.

[Insert Table 13 About Here]

We begin with a falsification exercise in Panel A by treating the bordering states of MMC-adopting states as if they were subject to the policy. The estimated coefficient on *False* is positive but statistically insignificant, suggesting that our baseline results are unlikely to be driven by pre-existing trends in neighboring states. Note that this geographic placebo test assigns false treatment to all units in border states, whereas the spillover analysis in Table 8 considers only units whose parent firm actually operates in an MMC state. As a large portion of border-state units lack firm-level exposure, the geographic placebo dilutes any relocation effect, so a null coefficient is consistent with the significant firm-level reallocation observed in Table 8.

Next, to further account for time-varying industry-specific factors, Panel B augments the baseline regression with 4-digit NAICS-by-year fixed effects. The coefficient of interest remains virtually unchanged, providing additional evidence that differential industry trends do not drive our results.

Third, to examine the external validity of our findings, Panel C re-estimates the baseline model using the full TRI sample, including units with missing information on their parent firms' DUNS numbers. The results closely mirror the baseline estimates, further supporting the robustness of our main findings.

In addition, we address the potential confounding effects of aggregate judicial activity. In Panel D, we re-estimate the baseline specification while controlling for the volume of court opinions, and the estimates remain stable and statistically similar to those in the main specification. One may also be concerned that unit size may confound the estimated effect of MMC adoption. To mitigate this concern, Panel E restricts the sample

to the TRI-InfoGroup-matched universe spanning 1997-2020 and explicitly controls for unit size, proxied by the logarithm of unit-level annual sales. The results show that total toxic emissions continue to decline following MMC adoption, although the effect becomes statistically insignificant. In contrast, the reduction in carcinogenic emissions remains both statistically and economically significant, with an estimated decrease of approximately 5% relative to the sample mean. By comparison, non-carcinogenic emissions exhibit a more moderate decline that is statistically insignificant. These results suggest that observed emission reductions, particularly for carcinogens, cannot be fully attributed to differences in unit scale.

Finally, in Panel F, we adopt an alternative definition of carcinogenic emissions, using both total and medium-specific releases of chemicals identified as carcinogens by the National Toxicology Program (NTP). The total-release coefficient aligns with the baseline but is statistically insignificant, whereas the air-specific component remains significant. This indicates that our results are robust to the NTP classification, with the strongest effects operating through the air-emission channel.

Taken together, these robustness checks support our baseline findings, confirming that MMC adoption leads to substantial reductions in toxic emissions.

5 Conclusion

This paper studies how firms respond to heightened environmental liability risk by exploiting the staggered adoption of medical monitoring claims across U.S. states. Unlike other environmental regulations that impose penalties on focal firms, MMCs require liable firms to cover residents' medical examination costs. We show that MMC adoption leads to a significant decline in toxic emissions, particularly for pollutants that are carcinogenic and released into the air, which are most strongly linked to health and reputation costs. These patterns suggest that firms adjust not only in volume but in the composition of emissions, responding strategically to the elevated environmental liability.

The effects, however, are not uniform across firms. The emission response is driven by single-unit and single-state firms, which are more directly exposed to state-level legal risk. In contrast, multi-unit, multi-state firms exhibit mild responses due to their ability to arbitrage. We unearth evidence consistent with within-firm reallocation: In response to MMC, single-state multi-unit firms cut emissions at high-polluting units,

while multi-state firms with operations in MMC-exempt states increase emissions in unaffected regions, suggesting arbitrage across states within the same organization. We provide additional evidence that multi-unit firms' responses to MMC adoption are affected by social pressure, internal capability, and campaign finance rules. In sum, we provide new evidence that multiunit firms engage in institutional arbitrage to internalize external liabilities.

References

- Akey, Pat and Ian Appel**, “The Limits of Limited Liability: Evidence from Industrial Pollution,” *Journal of Finance*, 2021, *76* (1), 5–55.
- Almeida, Heitor, Chang-Soo Kim, and Hwanki Brian Kim**, “Internal Capital Markets in Business Groups: Evidence from the Asian Financial Crisis,” *Journal of Finance*, 2015, *70* (6), 2539–2586.
- Aragón-Correa, J. Alberto, Alfred Marcus, and Nuria Hurtado-Torres**, “The Natural Environmental Strategies of International Firms: Old Controversies and New Evidence on Performance and Disclosure,” *Academy of Management Perspectives*, 2016, *30* (1), 24–39.
- Ash, Elliott, Massimo Morelli, and Matia Vannoni**, “More Laws, More Growth? Evidence from US States,” *Journal of Political Economy*, 2025, *133* (7), 2139–2179.
- Banerjee, Shantanu, Xin (Simba) Chang, Kangkang Fu, and George Wong**, “Corporate Environmental Risk and the Customer-Supplier Relationship,” *Working Paper*, 2014.
- Bartram, Söhnke M., Kewei Hou, and Sehoon Kim**, “Real Effects of Climate Policy: Financial Constraints and Spillovers,” *Journal of Financial Economics*, 2022, *143* (2), 668–696.
- Behrens, Mark A. and Christopher E. Appel**, “American Law Institute Proposes Controversial Medical Monitoring Rule in Final Part of Torts Restatement,” *Defense Counsel Journal*, 2020.
- Bellon, Aymeric**, “Does Private Equity Ownership Make Firms Cleaner? The Role of Environmental Liability Risks,” *Review of Financial Studies*, 2025, *38* (9), 2517–2556.
- Bénabou, Roland and Jean Tirole**, “Individual and Corporate Social Responsibility,” *Economica*, January 2010, *77* (305), 1–19.
- Berchicci, Luca, Glen Dowell, and Andrew A. King**, “Environmental Capabilities and Corporate Strategy: Exploring Acquisitions among US Manufacturing Firms,” *Strategic Management Journal*, 2012, *33* (9), 1053–1071.
- Berry, Heather, Aseem Kaul, and Narae Lee**, “Follow the Smoke: The Pollution Haven Effect on Global Sourcing,” *Strategic Management Journal*, 2021, *42* (13), 2420–2450.

- Bertrand, Marianne and Sendhil Mullainathan**, “Enjoying the Quiet Life? Corporate Governance and Managerial Preferences,” *Journal of Political Economy*, 2003, *111* (5), 1043–1075.
- , **Esther Duflo, and Sendhil Mullainathan**, “How Much Should We Trust Differences-in-Differences Estimates?,” *Quarterly Journal of Economics*, 2004, *119* (1), 249–275.
- Bisetti, Emilio, Stefan Lewellen, Arkodipta Sarkar, and Xiao Zhao**, “Smokestacks and the Swamp,” *Working Paper*, 2025.
- Bombardini, Matilde and Francesco Trebbi**, “Empirical Models of Lobbying,” *Annual Review of Economics*, 2020, *12* (1), 391–413.
- Brehm, John and James T. Hamilton**, “Noncompliance in Environmental Reporting: Are Violators Ignorant, or Evasive, of the Law?,” *American Journal of Political Science*, 1996, *40* (2), 444.
- Brunekreef, Bert and Stephen T. Holgate**, “Air Pollution and Health,” *The Lancet*, 2002, *360* (9341), 1233–1242.
- Bui, Linda T. M. and Christopher J. Mayer**, “Regulation and Capitalization of Environmental Amenities: Evidence from the Toxic Release Inventory in Massachusetts,” *Review of Economics and Statistics*, 2003, *85* (3), 693–708.
- Bushnell, James B., Stephen P. Holland, Jonathan E. Hughes, and Christopher R. Knittel**, “Strategic Policy Choice in State-Level Regulation: The EPA’s Clean Power Plan,” *American Economic Journal: Economic Policy*, 2017, *9* (2), 57–90.
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer**, “The Effect of Minimum Wages on Low-Wage Jobs*,” *Quarterly Journal of Economics*, 2019, *134* (3), 1405–1454.
- Chauvin, Jasmina and Christopher Poliquin**, “Supply-side Inducements and Resource Redeployment In Multiunit Firms,” *Strategic Management Journal*, 2024, *45*, 939–967.
- , **Carlos Inoue, and Christopher Poliquin**, “Resource Redeployment as an Entry Advantage in Resource-poor Settings,” *Strategic Management Journal*, 2024, pp. 1–32.
- Chava, Sudheer**, “Environmental Externalities and Cost of Capital,” *Management Science*, 2014, *60* (9), 2223–2247.

- Chen, Jason (Pang-Li)**, “Redeploying Dirty Assets: The Impact of Environmental Liability,” *Journal of Financial Economics*, 2025, 170.
- Chen, Qiaoyi, Zhao Chen, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Yi Xu**, “Regulating Conglomerates: Evidence from an Energy Conservation Program in China,” *American Economic Review*, 2025, 115 (2), 408–447.
- Chin, M. K., Donald C. Hambrick, and Linda K. Treviño**, “Political Ideologies of CEOs: The Influence of Executives’ Values on Corporate Social Responsibility,” *Administrative Science Quarterly*, 2013, 58 (2), 197–232.
- Colmer, Jonathan, Ralf Martin, Mirabelle Muûls, and Ulrich J. Wagner**, “Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence from the European Union Emissions Trading System,” *Review of Economic Studies*, May 2025, 92 (3), 1625–1660.
- Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker**, “Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings,” *American Economic Review*, 2015, 105 (2), 678–709.
- Dasgupta, Sudipto, Thanh D. Huynh, and Ying Xia**, “Joining Forces: The Spillover Effects of EPA Enforcement Actions and the Role of Socially Responsible Investors,” *The Review of Financial Studies*, 2023, 36 (9), 3781–3824.
- de Chaisemartin, Clément and Xavier D’Haultfoeulle**, “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects,” *American Economic Review*, 2020, 110 (9), 2964–2996.
- de Marchi, Scott and James T. Hamilton**, “Assessing the Accuracy of Self-Reported Data: an Evaluation of the Toxics Release Inventory,” *Journal of Risk and Uncertainty*, 2006, 32 (1), 57–76.
- Dickler, Teresa A., Timothy B. Folta, Marco S. Giarratana, and Juan Santaló**, “The Value of Flexibility in Multi-business Firms,” *Strategic Management Journal*, 2022, 43 (12), 2602–2628.
- Dowell, Glen, Stuart Hart, and Bernard Yeung**, “Do Corporate Global Environmental Standards Create or Destroy Market Value?,” *Management Science*, 2000, 46 (8), 1059–1074.

- Duchin, Ran and Denis Sosyura**, “Divisional Managers and Internal Capital Markets,” *Journal of Finance*, 2013, *68* (2), 387–429.
- , **Janet Gao, and Qiping Xu**, “Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution,” *Journal of Finance*, 2025, *80* (2), 699–754.
- Eesley, Charles and Michael J. Lenox**, “Firm Responses to Secondary Stakeholder Action,” *Strategic Management Journal*, 2006, *27* (8), 765–781.
- Fowle, Meredith, Mar Reguant, and Stephen P. Ryan**, “Market-Based Emissions Regulation and Industry Dynamics,” *Journal of Political Economy*, 2016, *124* (1), 249–302.
- Geistfeld, Mark A.**, “The Equity of Tort Claims for Medical Monitoring,” *Working Paper*, 2024.
- Gibson, Matthew**, “Regulation-Induced Pollution Substitution,” *The Review of Economics and Statistics*, 2019, *101* (5), 827–840.
- Goodman-Bacon, Andrew**, “Difference-in-Differences with Variation in Treatment Timing,” *Journal of Econometrics*, 2021, *225* (2), 254–277.
- Gormley, Todd A. and David A. Matsa**, “Growing Out of Trouble? Corporate Responses to Liability Risk,” *Review of Financial Studies*, 2011, *24* (8), 2781–2821.
- Greenstone, Michael**, “The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures,” *Journal of Political Economy*, 2002, *110* (6), 1175–1219.
- , “Estimating Regulation-Induced Substitution: The Effect of the Clean Air Act on Water and Ground Pollution,” *American Economic Review*, 2003, *93* (2), 442–448.
- Hadlock, Charles J. and Joshua R. Pierce**, “New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index,” *Review of Financial Studies*, 2010, *23* (5), 1909–1940.
- Hamilton, James T.**, “Pollution as News: Media and Stock Market Reactions to the Toxics Release Inventory Data,” *Journal of Environmental Economics and Management*, 1995, *28* (1), 98–113.

- Hanna, Rema**, “US Environmental Regulation and FDI: Evidence from a Panel of US-Based Multinational Firms,” *American Economic Journal: Applied Economics*, 2010, *2* (3), 158–189.
- Helfat, Constance E. and Kathleen M. Eisenhardt**, “Inter-temporal Economies of Scope, Organizational Modularity, and the Dynamics of Diversification,” *Strategic Management Journal*, 2004, *25* (13), 1217–1232.
- Hiatt, Shon R., Jake B. Grandy, and Brandon H. Lee**, “Organizational Responses to Public and Private Politics: An Analysis of Climate Change Activists and U.S. Oil and Gas Firms,” *Organization Science*, 2015, *26* (6), 1769–1786.
- Hou, Young and Christopher W. Poliquin**, “The Effects of CEO Activism: Partisan Consumer Behavior and its Duration,” *Strategic Management Journal*, 2023, *44* (3), 672–703.
- Kaplan, Steven N. and Luigi Zingales**, “Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?,” *Quarterly Journal of Economics*, 1997, *112* (1), 169–215.
- King, Brayden G.**, “A Political Mediation Model of Corporate Response to Social Movement Activism,” *Administrative Science Quarterly*, 2008, *53* (3), 395–421.
- Konar, Shameek and Mark A. Cohen**, “Information As Regulation: The Effect of Community Right to Know Laws on Toxic Emissions,” *Journal of Environmental Economics and Management*, January 1997, *32* (1), 109–124.
- Kuppuswamy, Venkat and Belén Villalonga**, “Does Diversification Create Value in the Presence of External Financing Constraints? Evidence from the 2007-2009 Financial Crisis,” *Management Science*, 2016, *62* (4), 905–923.
- Landrigan, Philip J.**, “Air Pollution and Health,” *The Lancet*, 2017, *2* (1), E4–E5.
- Lee, Narae and Aseem Kaul**, “Robbing Peter to Pay Paul: The Impact of California’s Cap-and-Trade Program on Toxic Emissions,” *Management Science*, 2025, p. mnsoc.2023.03560.
- Levine, Ross, Chen Lin, and Zigan Wang**, “Pollution and Human Capital Migration: Evidence from Corporate Executives,” *Working Paper*, 2018.

- Li, Xia**, “Physical Climate Change Exposure and Firms’ Adaptation Strategy,” *Strategic Management Journal*, 2025, 46 (3), 750–789.
- **and Caroline Flammer**, “Climate Risk Exposure and Firms’ Climate Strategies,” *Working Paper*, 2025.
- Li, Xiaoyang and Yue M. Zhou**, “Offshoring Pollution while Offshoring Production?,” *Strategic Management Journal*, 2017, 38 (11), 2310–2329.
- Luo, Jiao, Aseem Kaul, and Haram Seo**, “Winning Us With Trifles: Adverse Selection in the Use of Philanthropy as Insurance,” *Strategic Management Journal*, 2018, 39 (10), 2591–2617.
- Maksimovic, Vojislav and Gordon M. Phillips**, “Do Conglomerate Firms Allocate Resources Inefficiently Across Industries? Theory and Evidence,” *Journal of Finance*, 2002, 57 (2), 721–767.
- **and —**, “Conglomerate Firms and Internal Capital Markets,” *Handbook of Empirical Corporate Finance*, 2007, 1, 423–479.
- Matvos, Gregor, Amit Seru, and Rui C. Silva**, “Financial Market Frictions and Diversification,” *Journal of Financial Economics*, 2018, 127 (1), 21–50.
- **and —**, “Resource Allocation within Firms and Financial Market Dislocation: Evidence from Diversified Conglomerates,” *Review of Financial Studies*, 2014, 27 (4), 1143–1189.
- McLaughlin, Patrick A. and Oliver Sherouse**, “The Impact of Federal Regulation on the 50 States,” *Working Paper*, 2016.
- Mohai, Paul, David Pellow, and Timmons J. Roberts**, “Environmental Justice,” *Annual Review of Environment and Resources*, 2009, 34 (1), 405–430.
- Nordhaus, William D. and Zili Yang**, “A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies,” *American Economic Review*, 1996, pp. 741–765.
- Rajan, Raghuram, Henri Servaes, and Luigi Zingales**, “The Cost of Diversity: The Diversification Discount and Inefficient Investment,” *Journal of Finance*, 2000, 55 (1), 35–80.

- Roberts, Michael R. and Toni M. Whited**, “Endogeneity in Empirical Corporate Finance,” *Working Paper*, 2012.
- Sakhartov, Arkadiy V. and Timothy B. Folta**, “Resource Relatedness, Redeployability, and Firm Value: Resource Relatedness, Redeployability, and Firm Value,” *Strategic Management Journal*, 2014, *35* (12), 1781–1797.
- Scharfstein, David S. and Jeremy C. Stein**, “The Dark Side of Internal Capital Markets: Divisional Rent-Seeking and Inefficient Investment,” *Journal of Finance*, 2000, *55* (6), 2537–2564.
- Seru, Amit**, “Firm Boundaries Matter: Evidence from Conglomerates and R&D Activity,” *Journal of Financial Economics*, 2014, *111* (2), 381–405.
- Shapira, Roy and Luigi Zingales**, “Is Pollution Value-Maximizing? The DuPont Case,” *Harvard Environmental Law Review*, 2025.
- Shapiro, Joseph S. and Reed Walker**, “Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade,” *American Economic Review*, 2018, *108* (12), 3814–3854.
- Stein, Jeremy C.**, “Internal Capital Markets and the Competition for Corporate Resources,” *Journal of Finance*, 1997, *52* (1), 111–133.
- Sun, Liyang and Sarah Abraham**, “Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects,” *Journal of Econometrics*, 2021, *225* (2), 175–199.
- Toffel, Michael W. and Julian D. Marshall**, “Improving Environmental Performance Assessment: A Comparative Analysis of Weighting Methods Used to Evaluate Chemical Release Inventories,” *Journal of Industrial Ecology*, 2004, *8* (1-2), 143–172.
- van Binsbergen, Jules H., João F. Cocco, Marco Grotteria, and S. Lakshmi Naaraayanan**, “The Impact of Carcinogenic Risk Exposure on Housing Values: Estimates From Chemical Reclassifications,” *NBER Working Paper*, 2025.
- Whited, Toni M. and Guojun Wu**, “Financial Constraints Risk,” *Review of Financial Studies*, 2006, *19* (2), 531–559.

Wing, Coady, Seth M. Freedman, and Alex Hollingsworth, “Stacked Difference-in-Differences,” *NBER Working Paper*, 2024.

Xu, Qiping and Taehyun Kim, “Financial Constraints and Corporate Environmental Policies,” *Review of Financial Studies*, 2022, *35* (2), 576–635.

Figures and Tables

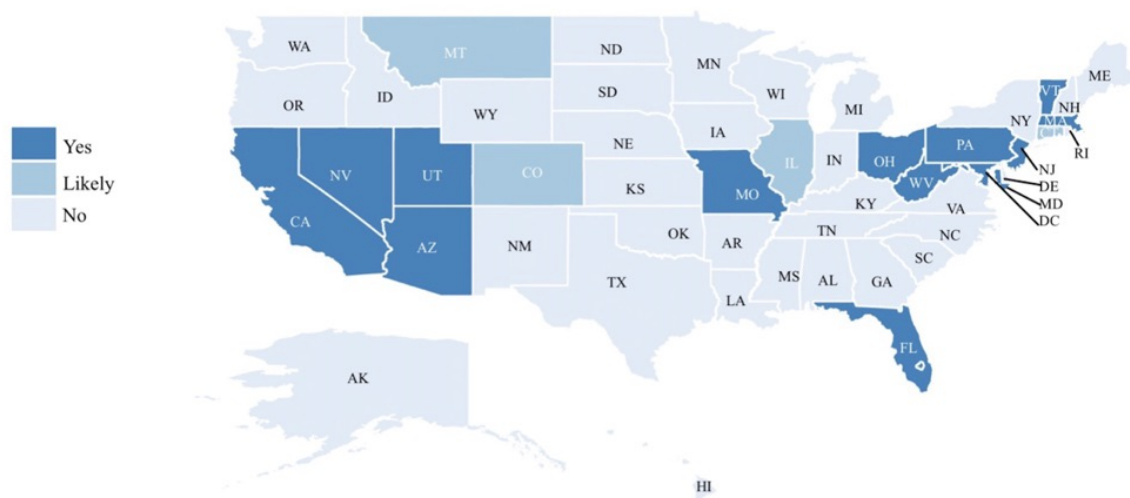
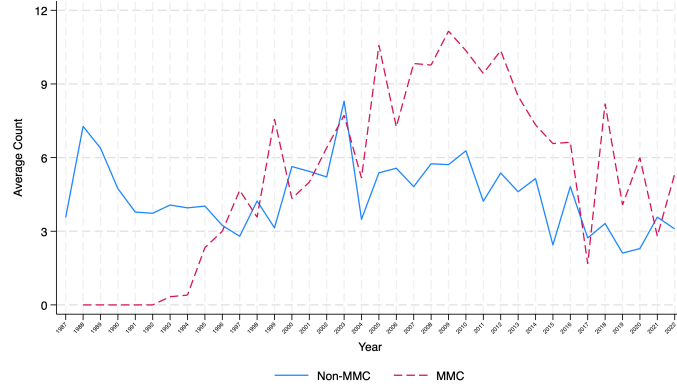
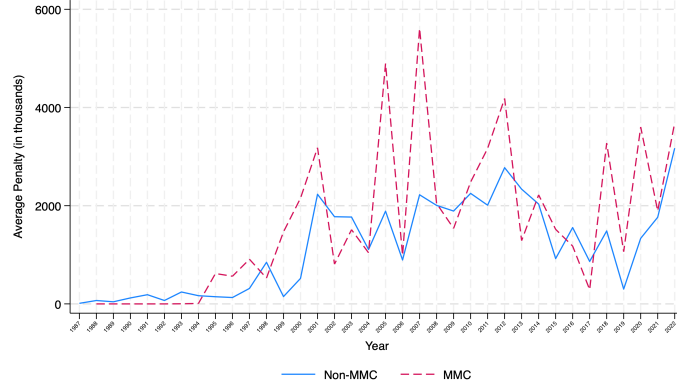


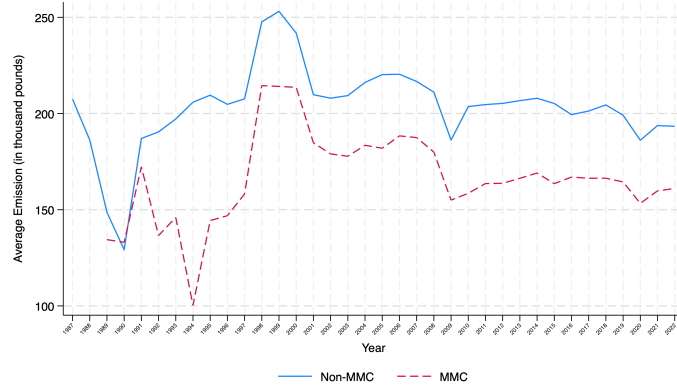
Figure 1: MMC Adoptions Across U.S. States. This figure depicts a map of the United States and shows the status of medical monitoring claim adoption as of 2022.



(a) Civil Judicial Actions: Count



(b) Civil Judicial Actions: Penalty



(c) TRI Toxic Emissions: Onsite Releases

Figure 2: Civil Judicial Actions and Toxic Emissions Across MMC-adopting and MMC-exempt States. This figure presents annual state-level trends during 1987 and 2022, comparing MMC-adopting and MMC-exempt States across three dimensions: (a) the average number of civil judicial actions, (b) the average aggregate penalties associated with these actions, and (c) the average onsite toxic releases reported by TRI units.

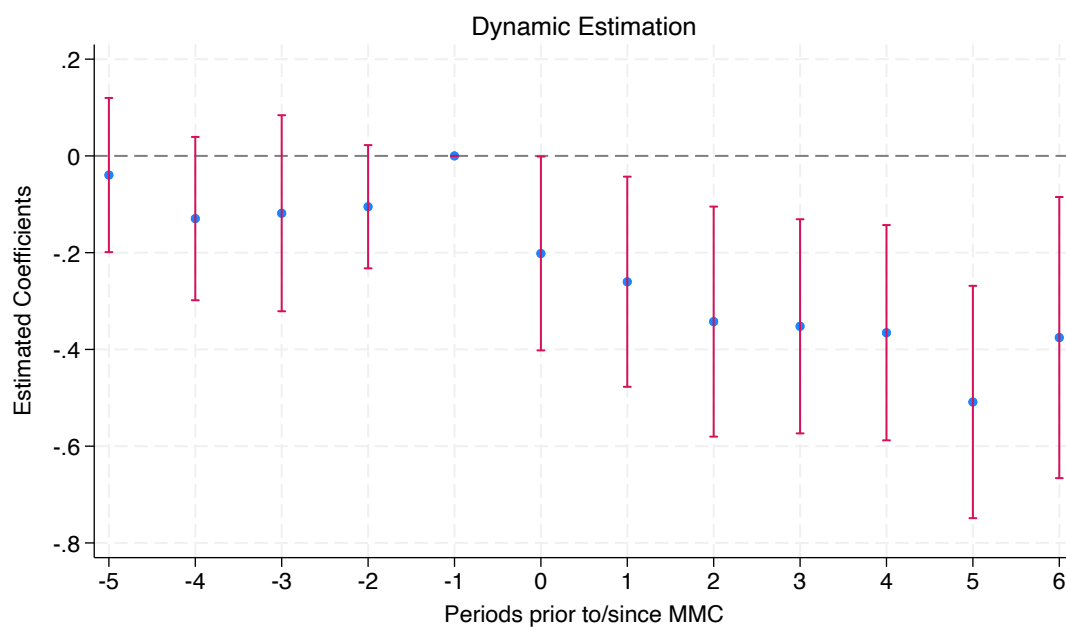


Figure 3: Dynamic Estimates. This figure shows the dynamic effects of MMC adoption using an event-study framework, with point estimates alongside 95% confidence intervals.

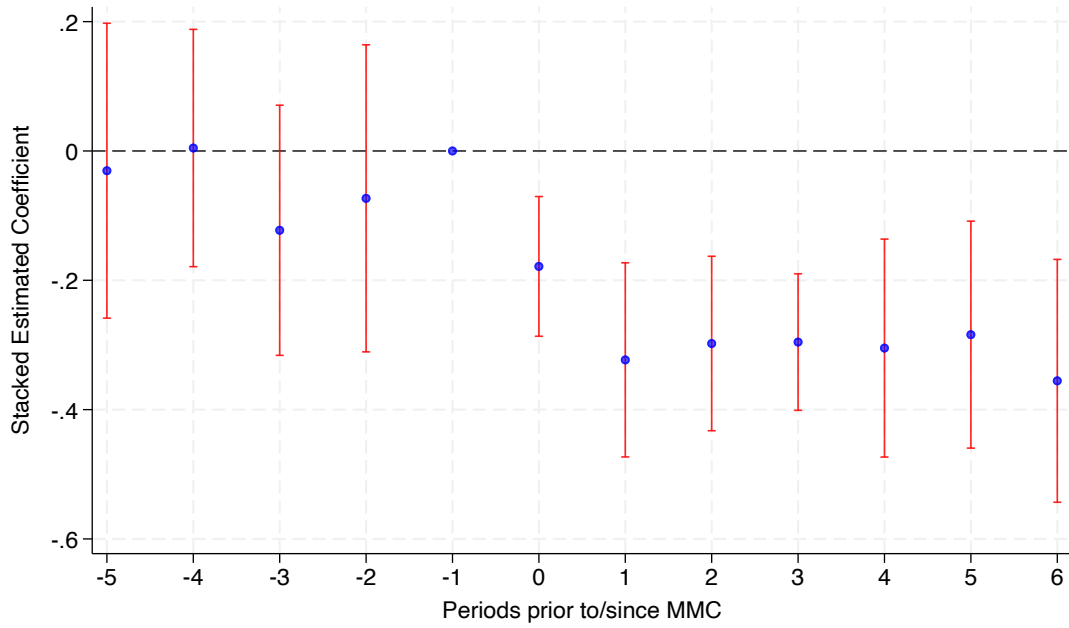


Figure 4: Stacked DID Estimates. This figure reports dynamic estimates using a stacked difference-in-differences design and applying weighting scheme suggested by Wing et al. (2024). Point estimates are reported, and the corresponding 95% confidence intervals are constructed using standard errors clustered at the state level.

Table 1: State-level Medical Monitoring Claim Adoption Summary

The table summarizes the stances of the U.S. states on medical monitoring claims. Panel A summarizes all adopting states, including those considered likely adopters, along with the corresponding year. Panel B summarizes states that have not recognized medical monitoring claims.

Panel A: Adopting States			
Yes			
No.	States	MMC	Year Since
1	AZ	Yes	1988
2	CA	Yes	1993
3	FL	Yes	1999
4	MD	Yes	2013
5	MA	Yes	2009
6	MO	Yes	2007
7	NV	Yes	2015
8	NJ	Yes	1987
9	OH	Yes	1994
10	PA	Yes	1997
11	UT	Yes	1993
12	VT	Yes	2019
13	WV	Yes	1999
14	DC	Yes	1984
Likely			
15	CO	Likely	1991
16	CT	Likely	2002
17	IL	Likely	2003
	IL	Likely	2016
18	MT	Likely	2000

Table 1: Medical Monitoring Claims Summary(Continued)

Panel B: Non-adopting States			
No.	States	No.	States
19	AL	36	ND
20	DE	37	OK
21	GA	38	SC
22	KY	39	TX
23	LA	40	VA
24	MI	41	WA
25	MS	42	AK
26	NC	43	HI
27	OR	44	ID
28	RI	45	KS
29	WI	46	ME
30	AR	47	NM
31	IN	48	NY
32	IA	49	SD
33	MN	50	TN
34	NE	51	WY
35	NH		

Table 2: Summary Statistics

This table presents summary statistics for the main unit-level variables for 1987-2022. *Toxic Emissions* denotes the annual toxicity-weighted emissions based on the Risk-Screening Environmental Indicators (RSEI) model. This is our main variable for toxic emissions. *Toxic_Carcinogen* and *Toxic_nonCarcinogen* measure the annual toxicity-weighted emissions specifically attributed to carcinogenic and non-carcinogenic risks, respectively. *Air* and *Water* measure emissions transmitted through air and water pathways, while *Land* and *Other* quantify those transmitted via land or other media. *StateCoverage* is the number of states in which a unit's parent firm operates TRI-reporting units, and *IntrastatePlant* is the number of units operated by the same firm within a given state.

Variables	Mean	SD	p25	p50	p75	N
Toxic Emissions	1710.940	8069.514	0	0.177	16.332	500,407
Toxic_Carcinogen	1583.288	7486.144	0	0.000	3.082	500,407
Toxic_nonCarcinogen	46.642	218.708	0	0.092	2.731	500,407
Air	1133.890	4957.428	0	0.135	14.085	500,407
Water	1.375	8.500	0	0.000	0.000	500,407
Land	25.868	198.900	0	0.000	0.000	500,407
Other	0.137	1.296	0	0.000	0.000	500,407
StateCoverage	7.347	8.467	1	4.000	10.000	500,407
IntrastatePlant	2.719	4.613	1	1.000	3.000	500,407

Table 3: Baseline: MMC and Unit-level Toxic Emission

This table reports regression estimates on the effect of medical monitoring claim (MMC) adoption on unit-level toxic emissions. The dependent variable is the logarithm of RSEI toxicity-weighted emissions. The key explanatory variable *MMC* is an indicator that equals one if the unit is located in a state that has adopted MMCs and zero otherwise. We incorporate two firm-level control variables: *StateCoverage* measures the number of states in which a parent firm operates TRI-reporting units, and *Log(IntrastatePlant)* denotes the logarithm of the number of units a parent firm operates in the same state. Various state-level control variables are also included. *GDPGrowth* and *UnempRate* represent state-level annual GDP growth and unemployment rate, respectively. *Log(PerIncome)* and *Log(Pop)* are the logarithms of state-level personal income and population. All regressions include year- and unit-fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)		
	(1)	(2)	(3)
MMC	−0.237** (0.096)	−0.231** (0.094)	−0.213** (0.099)
StateCoverage		0.047*** (0.011)	0.046*** (0.011)
Log(IntrastatePlant)		0.709*** (0.131)	0.672*** (0.130)
GDPGrowth			−0.823* (0.457)
UnempRate			−0.092*** (0.019)
PerIncome			0.246 (0.593)
Log(Pop)			0.140 (0.982)
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	500,407	500,407	487,212
Adj. R^2	0.738	0.738	0.738
Mean of Dep. Var.	11.063	11.063	11.090

Table 4: Carcinogenic Risk and Media of Emission

This table examines the roles of carcinogenic risks and transmission pathways in MMC-induced emission reductions. Panel A examines whether reductions differ between carcinogenic and non-carcinogenic emissions. The dependent variables $\text{Log}(\text{Toxic_Carcinogen})$ and $\text{Log}(\text{Toxic_nonCarcinogen})$ are the logarithms of annual toxicity-weighted carcinogenic and non-carcinogenic emissions, respectively. Panel B explores the medium through which emissions occur, using the RSEI model. Specifically, $\text{Log}(\text{Air})$ and $\text{Log}(\text{Water})$ denote the logarithms of emissions transmitted via air and water, while $\text{Log}(\text{Land})$ and $\text{Log}(\text{Other})$ measure emissions released through land or other media. All regressions follow the specification in Column (3) of Table 3, with the same controls and fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Carcinogen vs. non-Carcinogen				
Variables	Log(Toxic_Carcinogen) (1)	Log(Toxic_nonCarcinogen) (2)		
MMC	−0.335*** (0.111)	−0.154* (0.091)		
Firm Control	Yes	Yes		
State Control	Yes	Yes		
Year FE	Yes	Yes		
Unit FE	Yes	Yes		
Observations	487,212	487,212		
Adj. R^2	0.727	0.732		
Mean of Dep. Var.	6.063	9.864		

Panel B: Media of Emission				
Variables	Log(Air) (1)	Log(Water) (2)	Log(Land) (3)	Log(Other) (4)
MMC	−0.194** (0.094)	−0.015 (0.064)	−0.096 (0.066)	−0.041 (0.038)
Firm Control	Yes	Yes	Yes	Yes
State Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes	Yes
Observations	487,212	487,212	487,212	487,212
Adj. R^2	0.738	0.746	0.720	0.497
Mean of Dep. Var.	10.773	1.840	0.872	0.396

Table 5: Re-classifications of Carcinogens

This table examines whether the periodic Reclassification of Carcinogens (RoC) by the National Toxicology Program (NTP) affects the extent of emission reductions induced by MMCs. In Columns 1-3, the dependent variables are $\text{Log}(ToxicEmissions)$, $\text{Log}(Toxic_Carcinogen)$, and $\text{Log}(Toxic_nonCarcinogen)$, which represent the logarithms of annual toxicity-weighted total emissions, carcinogenic emissions, and non-carcinogenic emissions, respectively. In the same spirit as Gormley and Matsa (2011) and van Binsbergen et al. (2025), *RoC* is defined as a dummy variable indicating whether a plant produces chemicals newly identified as carcinogenic under the RoC. All regressions follow the specification in Column (3) of Table 3, with the same controls and fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)	Log(Toxic_Carcinogen)	Log(Toxic_ nonCarcinogen)
	(1)	(2)	(3)
MMC $\times$ RoC	-0.442*** (0.076)	-1.711*** (0.176)	-0.119* (0.062)
MMC	-0.042 (0.106)	0.316** (0.138)	-0.106 (0.091)
RoC	2.159*** (0.059)	5.223*** (0.135)	1.249*** (0.048)
Firm Control	Yes	Yes	Yes
State Control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes
Observations	487212	487212	487212
Adj. R^2	0.744	0.750	0.735
Mean of Dep. Var.	11.090	6.063	9.864

Table 6: The Role of Organizational Scope

This table examines the role of firms' organizational scope. Panel A compares pollution reductions between single-unit firms and multi-unit firms, where the binary variable *MultiUnit* is equal to 1 if the parent firm operates more than one TRI-reporting unit. Panel B restricts the sample to multi-unit firms and explores differences between firms with all units located within a single state (*SingleState*) and those operating across multiple states (*MultiState*). The dummy variable *MultiState* equals one if a firm has TRI-reporting units in more than one state. Panel C compares multi-state firms with single-state firms, including both single-unit firms and multi-unit single-state ones. *MultiState* is defined as in Panel B. In all panels, regression specifications include the same set of control variables and fixed effects as in Column (3) of Table 3. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Single-unit vs. Multi-unit			
Variables	Log(Toxic Emissions)		
	SingleUnit (1)	MultiUnit (2)	Full (3)
MMC	-0.478*** (0.122)	-0.114 (0.119)	-0.541*** (0.108)
MultiUnit $\times$ MMC			0.425*** (0.151)
MultiUnit			0.097 (0.106)
Firm Control	No	Yes	Yes
State Control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	106,222	381,699	487,212
Adj. R^2	0.726	0.750	0.738
Mean of Dep. Var.	10.738	11.192	11.090

Table 6: The Role of Organizational Scope (Continued)

Panel B: Multi-unit firms: Single-state vs. Multi-state			
Variables	Log(Toxic Emissions)		
	SingleState (1)	MultiState (2)	Full (3)
MMC	-1.019*** (0.288)	-0.060 (0.123)	-0.652*** (0.241)
MultiState $\times$ MMC			0.570** (0.237)
MultiState			0.528** (0.215)
Firm Control	Yes	Yes	Yes
State Control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	29,617	351,625	381,699
Adj. R^2	0.784	0.750	0.750
Mean of Dep. Var.	10.961	11.215	11.192

Panel C: Single-state vs. Multi-state			
Variables	Log(Toxic Emissions)		
	SingleState (1)	MultiState (2)	Full (3)
MMC	-0.575*** (0.093)	-0.060 (0.123)	-0.569*** (0.088)
MultiState $\times$ MMC			0.494*** (0.115)
MultiState			0.261** (0.107)
Firm Control	Yes	Yes	Yes
State Control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	134,305	351,625	487,212
Adj. R^2	0.732	0.750	0.738
Mean of Dep. Var.	10.787	11.215	11.090

Table 7: Intra-state Reallocation Within Firms

This table examines whether multi-unit firms engage in intra-state reallocation of toxic emissions in response to MMC adoption. The binary variable *Dirty* equals one if a unit ranks in the top 40th percentile of toxic emissions among all units operated by the same firm. Column (1) includes all multi-unit firms. Column (2) restricts the sample to single-state multi-unit firms, while Column (3) focuses on multi-state firms. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)		
	Full (1)	SingleState (2)	MultiState (3)
MMC	−0.033 (0.098)	−0.944*** (0.297)	0.010 (0.104)
MMC × Dirty	−0.166 (0.155)	−0.680*** (0.245)	−0.137 (0.156)
Dirty	2.700*** (0.049)	1.663*** (0.189)	2.750*** (0.053)
Firm Control	Yes	Yes	Yes
State Control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	381,699	29,617	351,625
Adj. R^2	0.764	0.787	0.764
Mean of Dep. Var.	11.192	10.961	11.215

Table 8: Cross-state Reallocation Within Firms

This table explores cross-state adjustment within multi-unit firms in response to MMC adoption. The sample is restricted to multi-state firms and units located in MMC-exempt states. *FMMC1* is a binary variable that equals 1 if the firm has operated any units in MMC-adopting states in the past two years. *FMMC2* measures the fraction of the firm's units located in MMC-adopting states within the past two years. All specifications include unit fixed effects and state-by-year fixed effects, which control for state-level time-varying factors. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)	
	(1)	(2)
FMMC1	0.208*** (0.071)	
FMMC2		1.110*** (0.231)
Firm Control	Yes	Yes
Year $\times$ State FE	Yes	Yes
Unit FE	Yes	Yes
Observations	219,751	219,751
Adj. R^2	0.754	0.755
Mean of Dep. Var.	11.287	11.287

Table 9: Financial Constraint

This table explores heterogeneity in multi-unit firms' responses to MMCs based on firm-level financial constraints. Column (1) restricts the sample to listed firms and re-estimates the specifications in Table 6, while Column (2) further adds firm-year controls (*PublicFirm Controls*), which are extracted from public firm financial statement, consisting of the logarithm of total assets, leverage, ROA, cash holdings, sales growth, asset tangibility, operating cash flow, and acquisition spending. In Column (3), we explore how financial constraints influence the differential reduction in toxic emissions associated with firms' organizational scope. Following the approach of Bartram et al. (2022), we construct a composite indicator of financial constraints by combining four commonly used proxies: the KZ index, SA index, WW index, and firm size. For each proxy, firms are classified as financially constrained if their values exceed the sample median for the constraint indices or fall below the median for firm size. The composite indicator classifies a firm as constrained if the majority of these four proxies categorize it as financially constrained ($FC = 1$); otherwise, it is classified as unconstrained ($FC = 0$). Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)		
	(1)	(2)	(3)
MultiUnit $\times$ MMC	0.779*** (0.259)	0.610** (0.247)	0.176 (0.336)
MMC	-0.674** (0.273)	-0.514* (0.279)	-0.138 (0.335)
MultiUnit	0.085 (0.178)	0.127 (0.193)	0.391 (0.286)
MultiUnit $\times$ FC $\times$ MMC			0.814** (0.385)
MultiUnit $\times$ FC			-0.416 (0.289)
FC * MMC			-0.674 (0.422)
FC			0.184 (0.315)
Firm Controls	Yes	Yes	Yes
State Controls	Yes	Yes	Yes
PublicFirm Controls	No	Yes	Yes
Year FE	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes
Observations	139287	123674	123674
Adj. R^2	0.749	0.756	0.756
Mean of Dep. Var.	11.222	11.238	11.238

Table 10: Environmental Capability

This table explores heterogeneity in multi-unit firms' responses to MMCs based on unit-level environmental abatement capabilities. Column (1) uses a dummy variable, *Process*, which equals one if the unit adopted any process-based abatement technology within the past five years. Column (2) relies on *NonProcess*, an indicator for the adoption of non-process-oriented technologies, including materials-based and operational abatement measures. In all columns, regression specifications include the same set of control variables and fixed effects as in Column (3) of Table 3. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)	
	(1)	(2)
MultiUnit $\times$ MMC $\times$ Process	-0.349** (0.140)	
MultiUnit $\times$ MMC $\times$ NonProcess		-0.345** (0.144)
MMC	-0.500*** (0.115)	-0.506*** (0.116)
MultiUnit	0.133 (0.116)	0.117 (0.119)
MultiUnit $\times$ MMC	0.469*** (0.170)	0.490*** (0.167)
Process	0.290*** (0.085)	
MMC $\times$ Process	0.129 (0.096)	
MultiUnit $\times$ Process	0.032 (0.093)	
NonProcess		0.230** (0.093)
MMC $\times$ NonProcess		0.100 (0.103)
MultiUnit $\times$ NonProcess		0.094 (0.109)
Firm Control	Yes	Yes
State Control	Yes	Yes
Year FE	Yes	Yes
Unit FE	Yes	Yes
Observations	394,490	394,490
Adj. R^2	0.776	0.776
Mean of Dep. Var.	11.039	11.039

Table 11: Social Activism

This table explores heterogeneity in multi-unit firms' responses to MMCs based on local social activism. We use two county-level proxies for social activism. Column (1) uses $\text{Log}(\text{NGO})$, the logarithm of the annual count of environmental non-government organizations (NGOs) headquartered in the county. Column (2) uses the county-level share of votes cast for the Democratic presidential candidate (*Democrat*), derived from election data spanning 2000 to 2022. In all columns, regression specifications include the same set of control variables and fixed effects as in Column (3) of Table 3. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)	
	(1)	(2)
MultiUnit $\times$ MMC $\times$ Log(NGO)	−0.135** (0.057)	
MultiUnit $\times$ MMC $\times$ Democrat		−1.998*** (0.554)
MMC	−0.002 (0.290)	−0.498 (0.398)
MultiUnit	0.309 (0.263)	0.929*** (0.273)
MultiUnit $\times$ MMC	1.035*** (0.364)	1.314*** (0.316)
MMC $\times$ Log(NGO)	−0.116* (0.060)	
MultiUnit $\times$ Log(NGO)	−0.055 (0.051)	
Democrat		1.046 (0.633)
MMC $\times$ Democrat		0.567 (0.696)
MultiUnit $\times$ Democrat		−1.222** (0.485)
Firm Control	Yes	Yes
State Control	Yes	Yes
Year FE	Yes	Yes
Unit FE	Yes	Yes
Observations	457,540	163,170
Adj. R^2	0.738	0.811
Mean of Dep. Var.	11.052	10.629

Table 12: Campaign Finance Rules

This table explores heterogeneity in multi-unit firms' responses to MMCs based on state-level campaign finance rules, specifically whether corporate contributions to political campaigns are prohibited. Column (1) employs a dummy variable, *ContriBan1*, which equals one if corporate contributions are prohibited. Column (2) employs a dummy variable, *ContriBan2*, that equals one if contributions are prohibited for either corporations or labor unions. In all columns, the regression specifications include the same set of control variables and fixed effects as in Column (3) of Table 3. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variables	Log(Toxic Emissions)	
	(1)	(2)
MultiUnit $\times$ MMC $\times$ ContriBan1	0.591** (0.270)	
MultiUnit $\times$ MMC $\times$ ContriBan2		0.601** (0.270)
MMC	-0.428*** (0.153)	-0.427*** (0.153)
MultiUnit	0.180 (0.154)	0.190 (0.156)
MultiUnit $\times$ MMC	0.137 (0.203)	0.132 (0.203)
ContriBan1	0.253 (0.162)	
MMC $\times$ ContriBan1	-0.186 (0.188)	
MultiUnit $\times$ ContriBan1	-0.111 (0.191)	
ContriBan2		0.219 (0.162)
MMC $\times$ ContriBan2		-0.186 (0.188)
MultiUnit $\times$ ContriBan2		-0.131 (0.197)
Firm Control	Yes	Yes
State Controls	Yes	Yes
Year FE	Yes	Yes
Plant FE	Yes	Yes
Observations	404,024	404,024
Adj. R^2	0.759	0.759
Mean of Dep. Var.	11.067	11.067

Table 13: Robustness Checks

This table presents regression results from a series of robustness checks. Panel A presents a falsification test by incorrectly assigning treatment status to units located in states bordering MMC-adopting states. The dummy variable *False* equals one for units in these falsely treated states. Panel B augments the baseline specification by including 4-digit NAICS-by-year fixed effects to control for time-varying industry-specific shocks. Panel C expands the sample to include all TRI-reporting units, including those lacking parent DUNS number information. Panel D examines whether state-level aggregate judicial intensity confounds the effects of MMC adoption. Following Ash et al. (2025), we collect a corpus of state appellate court opinions from LexisNexis and construct two proxies for aggregate judicial intensity. *CourtOpinionWords* is the logarithm of the total word count across all opinions, while *CourtPerOpinionWords* denotes the logarithm of average words per opinion. In Panel E, we restrict the sample to the TRIâInfoGroup matched universe spanning 1997-2020 and control for unit size. Specifically, *Log(Sales)* denotes the logarithm of annual sales at the unit level. Lastly, in Panel E, we use total releases, as well as medium-specific releases, of chemicals identified as carcinogens by the National Toxicology Program (NTP) as alternative proxies for toxic emissions. All specifications are similar to the baseline model in Table 3. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Falsification Test			
Variables	Log(Toxic Emissions)		
	(1)	(2)	(3)
False	0.099 (0.078)	0.099 (0.075)	0.101 (0.071)
Firm Control	No	Yes	Yes
State Control	No	No	Yes
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	500,407	500,407	487,212
Adj. R^2	0.738	0.738	0.738
Mean of Dep. Var.	11.063	11.063	11.090

Table 13: Robustness Checks (Continued)

Panel B: Time-varying Industry Trend			
Variables	Log(Toxic Emissions)		
	(1)	(2)	(3)
MMC	-0.208** (0.086)	-0.201** (0.085)	-0.183** (0.090)
Firm Control	No	Yes	Yes
State Control	No	No	Yes
Year $\times$ NAICS4 FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	499,705	499,705	486,522
Adj. R^2	0.746	0.746	0.746
Mean of Dep. Var.	11.065	11.065	11.093
Panel C: Full TRI Sample			
Variables	Log(Toxic Emissions)		
	(1)	(2)	
MMC	-0.235*** (0.073)	-0.200** (0.081)	
State Control	No	Yes	
Year FE	Yes	Yes	
Unit FE	Yes	Yes	
Observations	825,285	803,803	
Adj. R^2	0.725	0.725	
Mean of Dep. Var.	10.601	10.621	
Panel D: Aggregate Judicial Intensity			
Variables	Log(Toxic Emissions)		
	(1)	(2)	
MMC	-0.235** (0.107)	-0.237** (0.107)	
CourtOpinionWords	-0.045 (0.056)		
CourtPerOpinionWords			0.011 (0.049)
Firm Control	Yes	Yes	
State Control	Yes	Yes	
Year FE	Yes	Yes	
Unit FE	Yes	Yes	
Observations	433,684	433,684	
Adj. R^2	0.737	0.737	
Mean of Dep. Var.	11.210	11.210	

Table 13: Robustness Checks (Continued)

Panel E: Unit Size			
Variables	Log(Toxic Emissions)	Log(Toxic_Carcinogen)	Log(Toxic_nonCarcinogen)
	(1)	(2)	(3)
MMC	-0.038 (0.063)	-0.265*** (0.064)	-0.024 (0.052)
Log(Sales)	0.023*** (0.006)	0.021*** (0.005)	0.022*** (0.005)
State Control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unit FE	Yes	Yes	Yes
Observations	275138	275138	275138
Adj. R^2	0.807	0.794	0.808
Mean of Dep. Var.	10.034	5.327	8.961

Panel F: NTP Carcinogen Emissions					
Variables	Log(NTP)	Log(NTP Air)	Log(NTP Water)	Log(NTP Land)	Log(NTP Other)
	(1)	(2)	(3)	(4)	(5)
MMC	-0.041 (0.038)	-0.194** (0.094)	-0.015 (0.064)	-0.096 (0.066)	-0.041 (0.038)
Firm Control	Yes	Yes	Yes	Yes	Yes
State Control	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Observations	487212	487212	487212	487212	487212
Adj. R^2	0.758	0.761	0.634	0.511	0.344
Mean of Dep. Var.	1.026	2.099	0.176	0.035	0.019

A Internet Appendix

Table A1: Medical Monitoring Claim Adoption Court Cases

The table lists the court cases of the U.S. states on medical monitoring claim adoptions.

Yes						
No.	States	MMC	Year Since	Cases	Citation	
1	AZ	Yes	1988	Burns v Jaquays Mining Corp [1988]	156 Ariz. 375, 752 P.2d 28.	86
2	CA	Yes	1993	Potter v Firestone Tire & Rubber Co [1993]	6 Cal.4th 965, 25 Cal. Rptr. 2d 550, 863 P.2d 795.	856
3	FL	Yes	1999	Petito v AH Robins Co Inc [1999]	750 So. 2d 103	46
4	MD	Yes	2013	Exxon Mobil Corp v Albright [2013]	71 A.3d 30.	114
5	MA	Yes	2009	Donovan v Philip Morris USA Inc [2009]	914 NE2d 891.	57
6	MO	Yes	2007	Meyer ex rel Coplin v Fluor Corp [2007]	220 SW3d 712	36
7	NV	Yes	2015	Sadler v PacifiCare of Nev Inc [2015]	340 P.3d 1264, 130 Nev. Adv. Op 98.	42
8	NJ	Yes	1987	Ayers v Township of Jackson [1987]	525 A.2d 287.	286
9	OH	Yes	1994	Day v NLO [1994]	851 F. Supp 869.	55
10	PA	Yes	1997	Redland Soccer v Department of Army [1997]	548 Pa. 178, 696 A.2d 137.	90
11	UT	Yes	1993	Hansen v Mountain Fuel Supply Co [1993]	858 P.2d 970.	96
12	VT	Yes	2019	Sullivan v Saint-Gobain Performance Plastics Corp [2019]	431 F. Supp. 3d 448.	8
13	WV	Yes	1999	Bower v Westinghouse Elec Corp [1999]	206 W. Va. 133, 522 S.E.2d 424	107
14	DC	Yes	1984	Friends for All Children Inc v Lockheed Aircraft Corp [1984]	746 F.2d 816.	118
Likely						
15	CO	Likely	1991	Cook v Rockwell Intern Corp [1991]	755 F. Supp 1468	59
16	CT	Likely	2002	Martin v Shell Oil Co [2002]	180 F. Supp. 2d 313	13
17	IL	Likely	2003	Admit: Lewis v Lead Indus Ass'n [2003]	793 N.E.2d 869.	48
	IL	Likely	2016	Reject: In re Nat'l Collegiate Athletic Ass'n Student-Athlete Concussion Injury Litigation [2016]	314 FRD 580.	
18	MT	Likely	2000	Lamping v Am Home Prods Inc [2000]	No. DV-97-85786 WL 35751402.	

Table A2: Firm-Level Emission Responses among Multi-State Firms

This table reports firm-year regressions of total toxic emissions on MMC exposure among multi-state firms. $\text{Log}(\text{Agg Toxic Emissions})$ is the logarithm of the sum of a firm's unit-level toxic emissions. $FMMC1$ equals one if the firm operated at least one unit in an MMC-adopting state within the past two years, and $FMMC2$ captures the share of the firm's units located in adopting states over the same window. The sample refines to multi-state firms with at least one unit not subject to MMCs. *Firm Control* includes the number of states in which the firm operates and the number of units it operates. All specifications include firm- and year-fixed effects, and standard errors are clustered at the firm level.

Variables	Log(Agg Toxic Emissions)	
	(1)	(2)
FMMC1	0.059 (0.109)	
FMMC2		0.127 (0.247)
Firm Control	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	55021	55021
Adj. R^2	0.772	0.772
Mean of Dep. Var.	16.622	16.622

Table A3: Predicting State-level MMC Adoption

This table presents estimates of the effects of state-level legal and economic characteristics on MMC adoption during 1987-2022. Each column is estimated over the years for which the relevant covariates are available. In Panel A, we examine whether federal regulation, state regulations, and overall court output are associated with the likelihood of MMC adoption. To capture the influence of federal regulation, we use the *FRASE* index developed by McLaughlin and Sherouse (2016), which is available from 2000 to 2017. The *FRASE* (Federal Regulation and State Enterprise) index measures the extent to which federal regulations affect private-sector industries in each state, and a state's *FRASE* score reflects the relative impact of federal regulation on its economy. For state-level regulation and judicial output, we use the log of total word counts in state regulations and appellate court opinions, respectively, using data from Ash et al. (2025). In Panel B, we focus on a set of socioeconomic factors. *GDPGrowth* and *UnemploymentRate* denote the annual GDP growth and unemployment rate, respectively. *Log(PersonalIncome)* and *Log(Population)* are the logarithms of personal income and population at the state level. *Log(TRIunit)* denotes the logarithm of the number of TRI-reporting units, while *Log(ToxicRelease)* is the logarithm of toxic release at the state level. All the explanatory variables are measured with a lag relative to the MMC adoption indicator.

Panel A: Regulation and Overall Court Output			
Variables	MMC Adoption		
	(1)	(2)	(3)
FRASE	0.010 (0.011)		
StateRegulationWords		−0.915 (0.944)	
CourtOpinionWords			−3.037 (3.081)
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	833	705	1,363
Adj. R^2	0.061	0.147	0.017

Table A3: Predicting State-level MMC Adoption

Panel B: Economic Characteristics		
Variables	MMC Adoption	
	(1)	(2)
GDP Growth	−16.300 (16.587)	1.740 (5.222)
Unemployment Rate	−0.057 (0.075)	0.024 (0.133)
Personal Income	1.894 (1.901)	−11.950 (12.516)
Log(Population)	−0.895 (1.062)	−2.979 (5.663)
Log(TRIunit)	−0.041 (0.349)	−3.820 (3.981)
Log(Toxic Release)	0.035 (0.093)	0.984 (1.034)
State FE	No	Yes
Year FE	No	Yes
Observations	1,472	1,472
Adj. R^2	0.003	0.071

Table A4: Public Health Outcomes

This table presents the estimated effects of MMC adoption on state-level public health outcomes, measured by personal health care expenditures and cancer incidence rates. Panel A examines health care expenditures. In Column (1), the dependent variable is the logarithm of total personal health care expenditures (in millions of dollars), while Column (2) uses the logarithm of five-year average personal health care spending at the state level. All regressions in Panel A include state-level controls for GDP growth rate, unemployment rate, personal income, and population. Panel B evaluates the impact of MMC on cancer incidence rates. The dependent variable across all three columns is the average state-level cancer incidence rate, disaggregated by cancer site and age group, and averaged over post-MMC windows of five, ten, or fifteen years. Column (1) analyzes a five-year post-adoption window, Column (2) extends the window to ten years, and Column (3) uses a fifteen-year window. All specifications include state fixed effects, age-by-year fixed effects, cancer site-by-year fixed effects, and age-by-cancer site fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Personal Health Care Spending		
Variables	HC (1)	HC _[t+1,t+5] (2)
MMC	−0.026* (0.015)	−0.021* (0.012)
State Control	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes
Observations	1,440	1,392
Adj. R^2	0.999	0.999
Mean of Dep. Var.	9.862	9.998

Panel B: Cancer Incidence			
Variables	Crude Rate _[1,5] (1)	Crude Rate _[1,10] (2)	Crude Rate _[1,15] (3)
MMC	−0.369** (0.150)	−0.329*** (0.126)	−0.274*** (0.103)
State Control	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year × Age FE	Yes	Yes	Yes
Year × Cancer FE	Yes	Yes	Yes
Age × Cancer FE	Yes	Yes	Yes
Observations	1,009,038	1,031,963	1,039,515
Adj. R^2	0.978	0.982	0.984
Mean of Dep. Var.	31.482	30.284	29.701