Enforcing Clean Air, Achieving Climate Benefits

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Abstract

This study evaluates the greenhouse gas implications of environmental enforcement using the 2009 consent decree at Duke Energy's Gallagher coal plant as a natural experiment. The legally mandated shutdown or refueling of two generating units led to a sharp reduction in coal consumption starting in 2011. We apply a synthetic difference-in-differences (SDID) method to U.S. state-level panel data from 1998 to 2022 to estimate the causal impact of this intervention on CO_2 emissions at plant, state, and market scales. The results show significant and persistent reductions in total and coal-related emissions in Indiana, especially within the electric power sector. Extending the analysis to 14 additional states with similar coal unit retirements, we find consistent emission declines using a staggered SDID framework. Finally, we quantify the welfare implications of avoided emissions by estimating the environmental consumer surplus (ECS) using the social cost of carbon (SCC) framework. The results suggest substantial climate-related benefits associated with federal enforcement actions.

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1 Introduction

Coal-fired power plants have long been recognized as major sources of both local air pollutants and global greenhouse gas emissions (Graff Zivin and Neidell, 2013; Cummiskey et al., 2019; Strasert et al., 2019; Sampedro et al., 2021; Filonchyk and Peterson, 2023). In the U.S., coal combustion accounts for a disproportionate share of energy-related carbon dioxide (CO_2) emissions, alongside co-pollutants such as sulfur dioxide (SO_2), nitrogen oxides (NO_x), and mercury (EPA, 2009b; Burtraw and Woerman, 2013). According to the U.S. Congressional Budget Office, coal-fired electricity generation alone accounted for over 60% of the electric power sector's CO_2 emissions in 2021 (Congressional Budget Office, 2023).

Previous research has emphasized the urgency of reducing coal use to meet national and global climate targets (Burtraw and Woerman, 2013; Davis and Socolow, 2014; Murray and Maniloff, 2015; Gillingham and Stock, 2018; Net, 2021). Beyond market-based approaches, recent research shows that non-price regulatory interventions can deliver substantial emission reductions, particularly when targeting aging, inefficient coal infrastructure (Burtraw and Woerman, 2013; Sgarciu et al., 2023; Campos Morales et al., 2024; Gathrid et al., 2025). These findings suggest that enforcement-based policies may complement carbon pricing in accelerating decarbonization.

To illustrate how these enforcement mechanisms operate, we turn to a prominent case: the 2009 consent decree against Duke Energy's Gallagher Generating Station in Indiana. Starting in late 1999, the U.S. Environmental Protection Agency (EPA) announced civil complaints against 7 electricity-producing utilities for violations at coal-fired power plants they operated (EPA 2023). One notable enforcement actions under the U.S. Clean Air Act was the 2009 consent decree involving Duke Energy's Gallagher Generating Station in Indiana. The EPA and the Department of Justice (DOJ) took legal action against Duke Energy (then Cinergy) for modifying two units without required permits or pollution controls—violating the Act's New Source Review (NSR) provision (EPA, 2009a). The court ruled in favor of the government, triggering a consent decree that forced Duke Energy (formerly Cinergy) to either shut down Units 1 and 3 or refuel to natural gas and install sorbent injection on the remaining units (EPA, 2009a).

Generally, NSR enforcement actions required retrofitting scrubbers, fuel changes, and/or the shutdown of generators (EPA, 2023). As such, the Gallagher settlement provides an instance of a legally mandated refueling that resulted in the shutdown of two generators and large-scale CO_2 emissions reductions (EPA, 2009b). Other scholars have highlighted the uniqueness of such structural transitions, noting that regulatory enforcement rarely achieves decarbonization goals unless it compels technological or fuel substitution (Aldy and Pizer, 2015; Fowlie and Muller, 2019; Prest et al., 2024). This unique enforcement episode forms the basis of our empirical analysis, in which we estimate its impact on CO_2 emissions using state-level data and a synthetic difference-in-differences (SDID) approach.

Our analysis uses state-level panel data from 1998 to 2022 to construct a counterfactual emissions trajectory for Indiana had the Gallagher settlement not occurred. We focus both on total energy-related CO_2 emissions and disaggregated sources by fuel and economic sector. This setting offers an ideal quasi-experimental case: Indiana received a sharp, exogenous policy shock, while comparable states did not undergo similar fuel-switching events during the same period but faced structural market changes (e.g., natural gas expansion) that resulted in downward trends in net CO_2 emissions for the sector overall (Abadie et al., 2010; Arkhangelsky et al., 2021).

Our results indicate that the consent decree led to significant and sustained reductions in Indiana's total and coal-related CO_2 emissions, concentrated in the electric power and industrial sectors. These effects align with recent findings that large-scale plant retirements or repowering tend to produce deep emissions reductions when accompanied by binding legal mandates (Cullen, 2013; Bistline et al., 2025). We further extend the analysis by incorporating 14 other states that undertook major coal unit retirements, using a staggered SDID framework that accounts for variation in treatment timing (Arkhangelsky et al., 2021; Clarke et al., 2024). We compare different approaches for covariate adjustment and find that the projection method proposed by Kranz (2022) improves estimation precision in staggered settings. This methodological insight contributes to a growing literature on best practices in causal inference under staggered adoption (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021).

In addition to estimating emissions reductions, we complement our causal analysis with a welfare-based evaluation of the policy's environmental benefits. Specifically, we quantify the environmental consumer surplus (ECS) generated by reduced carbon emissions using the social cost of carbon (SCC) framework (Greenstone and Jack, 2015; Nordhaus, 2017; Auffhammer, 2018; Cai and Lontzek, 2019; Rennert et al., 2022). This approach allows us to translate avoided emissions into a monetized measure of climate-related damages averted. By applying this method to both Indiana and the staggered multi-state sample, we estimate the net present value (NPV) of cumulative societal gains over a ten-year horizon. Our findings suggest that regulatory enforcement can yield \$15.77 billion in environmental benefits, reinforcing the economic case for compliance with federal emissions mandates. This welfare-based extension complements our emissions analysis and situates our results within broader discussions of regulatory cost-effectiveness and carbon and air quality policy evaluation (Greenstone and Hanna, 2014; Auffhammer, 2018; Rennert et al., 2022).

Overall, this study contributes to the broader literature on climate policy and regulatory enforcement. While carbon pricing remains central to many national strategies, our findings highlight the potential for targeted command-and-control interventions to produce ancillary climate benefits, especially when aimed at legacy fossil fuel infrastructure. As policymakers seek to decarbonize the power sector and meet net-zero goals, understanding the emission impacts of environmental enforcement provides a complementary lens to evaluate decarbonization strategies.

The remainder of this paper is organized as follows. Section 2 provides background on the NSR enforcement and the Gallagher consent decree. Section 3 outlines the empirical strategy, including the SDID estimator. Section 4 describes the data and summary statistics. Section 5 presents the main results and sectoral analysis, and Section 6 provides the welfare analysis. Finally, Section 7 concludes with policy implications.

2 Background

This section provides institutional context on the Clean Air Act's NSR program and the specific enforcement action at Duke Energy's Gallagher Generating Station in Indiana. Under NSR provisions, major modifications to existing power plants that increase emissions require installation of best-available control technology and updated permits. Beginning in the late 1990s, the U.S. EPA, often in coordination with the DOJ, initiated a series of enforcement actions against coal-fired utilities that had undertaken such modifications without complying with NSR requirements (EPA, 2009a,b, 2023).

One of the most prominent cases in this enforcement wave concerned Duke Energy's (the Cinergy's) Gallagher Generating Station in New Albany, Indiana. Built in the 1950s, the plant consisted of four coal-fired units that had undergone substantial refurbishment over time. In 2009, EPA and DOJ filed suit alleging the Duke had carried out major modifications on Unit 1 and 3 without obtaining the necessary permits or installing required pollution controls, in violation of NSR and the Indiana State Implementation Plan (EPA, 2009a). After nearly a decade of litigation, a federal jury in Indianapolis ruled in 2009 that these modifications led to significant increases in CO_2 emission, along with harmful co-pollutants such as SO_2, NO_x, and mercury, without corresponding controls, confirming Duke's liability (EPA, 2009a).[1]

In response to the verdict, a partial consent decree was entered in late 2009. The settlement required Duke to either repower Units 1 and 3 to burn natural gas or permanently retire them, and to install Dry Sorbent Injection (DSI) technology on Units 2 and 4 (EPA, 2009b). These provisions were expected to cut CO_2 emissions and decree also mandated a $1.75 million civil penalty and $6.25 million in environmental mitigation projects, including land conservation, hybrid vehicle conversions, and renewable energy upgrades, reflecting EPA's practice of pairing enforcement with broader environmental benefits (EPA, 2009b).

Compared with many other NSR settlements in the 2000s, which primarily required installation of end-of-pipe controls such as scrubbers, the Gallagher decree was unusually stringent in conditioning compliance on either permanent shutdown or full conversion to natural gas (EPA, 2009a,b, 2023). This requirement induced a structural shift in the plant's fuel mix rather than incremental emissions abatement. The substantial decline in coal use at Gallagher beginning in 2011—documented in our data section—captures the implementation of these mandated changes and forms the basis for our subsequent empirical analysis of their impact on state-level energy-related CO_2 emissions.

3 Empirical Strategy

We estimate the causal effect of Indiana's Gallagher coal plant intervention on carbon emissions using the SDID estimator proposed by Arkhangelsky et al. (2021). The SDID approach generalizes traditional DID and SC methods by constructing a weighted two-way fixed effects estimator that relaxes the parallel trends assumption through simultaneous re-weighting of units and time periods. This enhances robustness to unobserved confounding and non-parallel trends [2]. In our application, the treated unit is Indiana, where the Gallagher coal plant underwent a legally mandated shutdown or refueling following the consent decree.

The outcome variable Y_{it} represents annual energy-related CO_2 emissions for each state $i \in \{1, ..., N\}$ and year $t \in \{1, ..., T\}$, capturing the carbon implications of changes in fuel use. Let $W_{it} \in \{0, 1\}$ denote the treatment indicator, where $W_{it} = 1$ if state i is treated at time t (i.e., post-Gallagher closure in Indiana) and $W_{it} = 0$ otherwise. Following Arkhangelsky et al. (2021), the

[1] Figure B1 shows the location of the Gallagher Plant in southern Indiana.

[2] Our methodological interpretations for SDID are informed by the formulations presented in Arkhangelsky et al. (2021) and Clarke et al. (2024).

SDID estimator computes the average treatment effect on the treated (ATT), denoted τ, by solving the following weighted least squares problem:

$$(\hat{\tau}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min_{\tau,\mu,\alpha,\beta} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - \tau W_{it}\right)^2 \hat{\omega}_i \hat{\lambda}_t, \tag{1}$$

where $\hat{\omega}_i$ and $\hat{\lambda}_t$ are the estimated unit and time weights, respectively, optimized over the pre-treatment period. These weights localize the estimation to the most comparable states and periods. Comparability in this case refers primarily to generation or fuel input mix within a state. We note that energy markets and energy dispatch extend beyond state lines, but a state-level aggregation captures policy incentives and other state-level factors that can influence the generation mix.

The unit weights $\hat{\omega}_i$ are chosen by solving:

$$(\hat{\omega}_0, \hat{\omega}) = \arg\min_{\omega_0,\omega} \sum_{t=1}^{T_{\text{pre}}} \left(\omega_0 + \sum_{i \in \text{control}} \omega_i Y_{it} - \frac{1}{N_{\text{treated}}} \sum_{i \in \text{treated}} Y_{it} \right)^2 + \zeta^2 T_{\text{pre}} \|\omega\|^2, \tag{2}$$

subject to $\sum_{i \in \text{control}} \omega_i = 1$ and $\omega_i \geq 0$. The parameter ζ controls the degree of regularization (Arkhangelsky et al., 2021).

The time weights $\hat{\lambda}_t$ are similarly estimated as:

$$(\hat{\lambda}_0, \hat{\lambda}) = \arg\min_{\lambda_0,\lambda} \sum_{i \in \text{control}} \left(\lambda_0 + \sum_{t=1}^{T_{\text{pre}}} \lambda_t Y_{it} - \frac{1}{T_{\text{post}}} \sum_{t=T_{\text{pre}}+1}^{T} Y_{it} \right)^2 + \zeta^2 N_{\text{control}} \|\lambda\|^2, \tag{3}$$

subject to $\sum_{t=1}^{T_{\text{pre}}} \lambda_t = 1$ and $\lambda_t \geq 0$ [3].

These weights enable a weighted DID estimator for ATT:

$$\hat{\tau} = \hat{\delta}_{\text{treated}} - \sum_{i \in \text{control}} \hat{\omega}_i \hat{\delta}_i, \tag{4}$$

where

$$\hat{\delta}_{\text{treated}} = \frac{1}{N_{\text{treated}}} \sum_{i \in \text{treated}} \hat{\delta}_i = \frac{1}{N_{\text{treated}}} \sum_{i \in \text{treated}} \left(\frac{1}{T_{\text{post}}} \sum_{t=T_{\text{pre}}+1}^{T} Y_{it} - \sum_{t=1}^{T_{\text{pre}}} \hat{\lambda}_t Y_{it} \right). \tag{5}$$

To improve precision and reduce confounding, we include time-varying covariates X_{it} by

[3] We adopts a minimal regularization parameter, $\zeta = 1 \times 10^{-6} \hat{\sigma}$, to ensure a unique solution for the time weights (Clarke et al., 2024).

applying a residualization step. We regress Y_{it} on covariates X_{it} to derive γ, and then compute residualized outcomes:

$$\hat{Y}_{it} = Y_{it} - X'_{it}\hat{\gamma}. \tag{6}$$

The SDID estimator is then applied to $\hat{Y}_{it}$ (Arkhangelsky et al., 2021; Clarke et al., 2024). In our case, these covariates include real GDP and population growth, which capture changes in electricity demand and industrial activity that could otherwise confound the relationship between regulatory enforcement and emission outcomes.

To assess the statistical significance of the estimated treatment effects, we implement a placebo inference procedure. Following Arkhangelsky et al. (2021) and Clarke et al. (2024), we generate placebo estimates by applying the SDID estimator to units in the donor pool (i.e., control states) as if they had received the treatment. Specifically, we iteratively assign the treatment to each control unit and compute the corresponding placebo ATT under the same pre- and post-treatment periods used for Indiana. This generates a distribution of placebo treatment effects $\{\hat{\tau}_p\}_{p=1}^{P}$, which serves as an empirical null distribution under the assumption of no treatment effect.

The variance of the estimator is then computed as $\hat{V}_{\text{placebo}}(\hat{\tau}) = \text{Var}(\hat{\tau}_p)$, allowing for the construction of robust confidence intervals as

$$\hat{\tau} \pm z_{\alpha/2}\sqrt{\hat{V}_{\text{placebo}}(\hat{\tau})}. \tag{7}$$

In our application, we use this placebo distribution to derive standard errors and report p-values based on the percentile rank of the true ATT estimate within the placebo distribution. This procedure helps to account for finite-sample uncertainty and relaxes reliance on asymptotic approximations, which may be problematic in small donor pools or when the treated unit has unique characteristics (Abadie et al., 2010; Clarke et al., 2024). The placebo exercise also serves as an intuitive falsification check: under the null of no treatment effect, the treated unit's estimated ATT should resemble placebo estimates generated for untreated units. We later use this framework to assess whether Indiana's post-treatment trajectory is consistent with such a null pattern.

4 Data

To estimate the impact of state-level policy, we collect the panel dataset that tracks annual CO_2 emissions and key economic and demographic variables for each U.S. state and the District of

Columbia from 1998 to 2022. Our primary outcome variable is total energy-related CO_2 emissions, measured in million metric tons (MMT) per year, obtained from the U.S. Energy Information Administration (EIA) (U.S. Energy Information Administration, 2024). These emissions figures are compiled from fossil fuel combustion across five major sectors: residential, commercial, industrial, transportation, and electric power generation. Importantly, the EIA assigns emissions to the state where combustion physically occurs rather than the state where the energy is ultimately consumed (U.S. Energy Information Administration, 2023). This geographic attribution is particularly relevant when analyzing state-level policy effects, as it ensures that observed emissions reflect actual in-state fuel usage and regulatory jurisdiction.

The emission estimates provided by the EIA are derived by combining data on fossil fuel consumption—sourced from the State Energy Data System (SEDS)—with standardized fuel-specific carbon coefficients (U.S. Energy Information Administration, 2023). The EIA's methodology accounts for the type and quantity of fuel used in each sector, providing a consistent and comprehensive measure of CO_2 emissions that is comparable across states and years. Because the estimation process does not include emissions from biomass or land use change, the resulting data focus exclusively on fossil-fuel-related emissions, which is consistent with the regulatory domains most relevant to this study–namely, federal Clean Air Act mandates and associated air-quality compliance requirements, as well as state-level energy policies and other regulatory constraints that shape the energy mix and overall emissions.

To construct a credible counterfactual in our SDID framework, we supplement the EIA emission data with covariates that capture state-level economic activity and population dynamics. We include real gross domestic product (GDP), sourced from the Bureau of Economic Analysis (BEA), to control for changes in industrial output and economic growth that may affect emissions independently of policy interventions (Stern, 2004; Ang, 2007; Murray and Maniloff, 2015; U.S. BEA, 2025). In addition, we compute the annual population growth rate using state-level population data from the Federal Reserve Bank (Federal Reserve Bank of St. Louis, 2024). Population dynamics are a critical confounder, as growing populations often imply increased energy demand, infrastructure expansion, and vehicle usage—all of which can influence the level and trajectory of emissions (Dietz and Rosa, 1997; Shi, 2003; O'Neill et al., 2012; Huntington and Liddle, 2022). Including these covariates allows us to account for observable heterogeneity across states, thereby improving the plausibility of the identification strategy and reducing omitted variable bias in the treatment effect estimation.

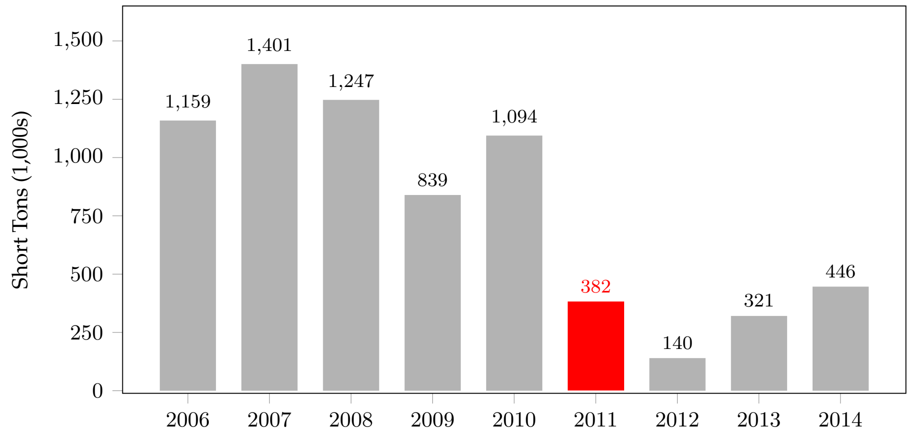


Figure 1: Coal Consumption at Gallagher Power Plant. The sharp decline in 2011 reflects the implementation phase of the 2009 consent decree.

The final dataset is a balanced panel of 37 cross-sectional units—selected 36 U.S. states and the District of Columbia—over a 25-year period from 1998 to 2022, yielding 925 state-year observations. As noted in Table B1, states directly subject to comparable enforcement actions were excluded from the donor pool to avoid contamination of the control group. Beyond these exclusions, we also considered the possibility of cross-state linkages when constructing the control group, recognizing that policy or operational change in one state could, in principle, induce correlated adjustments in neighboring states' energy use or emissions. To address this concern, we examined pre-treatment comovement patterns and post-treatment diagnostics across nearby states and found no evidence of coordinated shift around the intervention year. This supports the assumption that any cross-state spillovers were limited, allowing the remaining donor states to serve as credible counterfactuals.[4].

Although the Gallagher consent decree was finalized in 2009, we designate 2011 as the treatment year in our analysis. This timing reflects the actual implementation phase of the decree, during which significant operational changes took place at the Gallagher power plant. As shown in Figure 1, coal consumption at the facility remained relatively stable through 2010, averaging over 1 million short tons annually [5] . In contrast, 2011 witnessed a dramatic decline in coal use to 382 thousand short tons—a nearly 65% drop from the previous year. This sharp reduction indicates the onset of structural changes associated with the consent decree. By selecting 2011 as the treatment year, we capture the emissions trajectory immediately preceding these transformative shifts, while avoiding anticipatory or transitional dynamics that might confound the analysis.

[4]See Appendix A for a detailed discussion of linkage considerations and supplementary analyses

[5]The Gallagher consent decree (EPA, 2009b) outlined a timeline for the required actions to be taken in generators 1 and 3. Starting in 2009, the Gallagher plant was required to reduce CO_2 and SO_2 emissions. This phase of reductions lasted until January 30, 2011, after which time allowable emission levels became more stringent.

	Pooled sample		Treated group		Control group	
	pre	post	pre	post	pre	post
Log Real GDP	11.88	12.13	12.59	12.78	11.87	12.11
Population growth (%)	1.19	0.70	2.03	1.80	1.17	0.67
Total CO_2 emissions (MMT)	101.18	91.51	230.25	183.07	97.60	93.46
Fuel specific emission (MMT)						
Coal emissions	34.61	23.68	145.63	93.36	31.52	21.74
Natural gas emissions	22.55	26.99	28.04	40.76	22.30	26.61
Petroleum emissions	44.20	40.85	56.58	48.94	43.67	40.62
Sectoral specific emission (MMT)						
Commercial emissions	4.12	4.25	5.72	5.59	4.07	4.21
Electric power emissions	38.71	31.11	118.50	86.14	36.49	29.58
Industrial emissions	18.07	17.43	52.35	43.71	17.12	16.70
Residential emissions	6.57	6.03	9.51	8.31	6.48	5.97
Transportation emissions	33.72	32.70	44.17	39.32	33.43	32.51

Table 1: Covariate and outcome means by group (1998–2022). Real GDP is expressed in constant 2017 dollars, allowing for inflation-adjusted comparisons across years. The table reports mean values for key variables across the pooled sample, treated state (Indiana), and control states. "Pre" refers to the period prior to the 2011 treatment year against Indiana's Gallagher coal plant, and "Post" refers to the period from 2011 onward.

Table 1 presents covariate and outcome means for the pooled sample, the treated group (Indiana), and the control group, separately for the pre- and post-treatment periods. In Table 1, Indiana stands out for its substantially higher carbon intensity. In the pre-treatment period, total CO_2 emissions in Indiana averaged 230.25 MMT, more than double the control group average of 97.60 MMT. The gap is especially wide in coal-related emissions (145.63 vs. 31.52 MMT) and electric power emissions (118.50 vs. 36.49 MMT), consistent with Indiana's reliance on coal-fired generation. The state also exhibits elevated industrial emissions and lower reliance on natural gas and petroleum relative to control states. Following the 2011 treatment year, Indiana's emissions declined across all major categories. In the post-treatment period, the state's average total CO_2 emissions fell to 183.07 MMT, a reduction of over 40 MMT from the pre-period level. Coal emissions dropped substantially (from 145.63 to 93.36 MMT), and electric power emissions similarly declined (from 118.50 to 86.14 MMT), suggesting significant shifts in the state's energy mix and emissions profile. While Indiana remained more carbon-intensive than control states, the post-policy decline suggests a meaningful change associated with the treatment.

In contrast, economic and demographic indicators show modest differences. Indiana's pre-treatment average log real GDP is 12.59, close to the control group's 11.87, and its population growth rate (2.03%) is moderately higher than that of the control group (1.17%). These similarities help ensure comparability in baseline characteristics before the enforcement event.

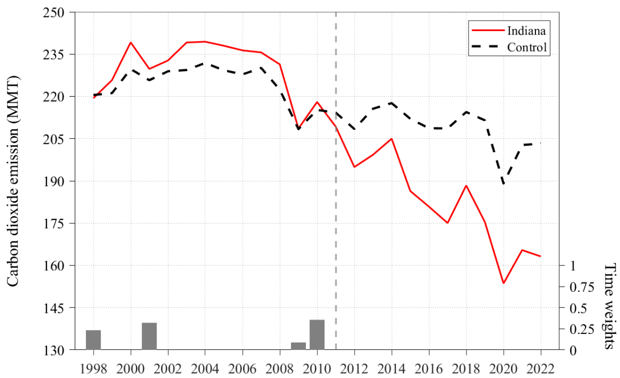
5 Results

5.1 Synthetic difference in difference estimation

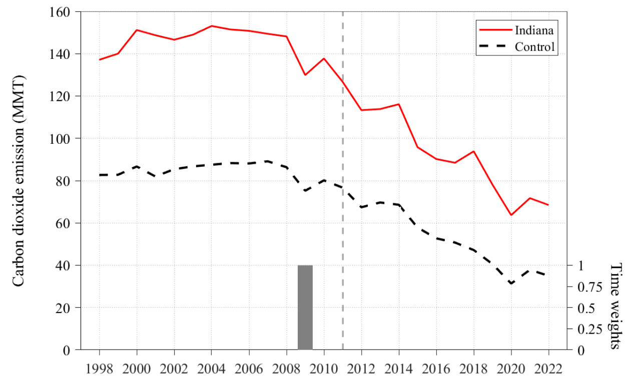
Figure 2 presents the SDID estimates comparing Indiana to a synthetic control group across multiple categories of energy-related CO_2 emissions. Panel (a) displays the trajectory of total emissions, while Panels (b) through (d) disaggregate these emissions into coal, natural gas, and petroleum sources, respectively. As shown in Panel (a), Indiana's total energy-related CO_2 emissions began to diverge markedly from the synthetic control group shortly after the 2011 treatment issued against the Gallagher coal-fired power plant. According to the settlement terms, Duke Energy was required to either permanently shut down or re-power Units 1 and 3 to burn natural gas, and to install pollution controls on the remaining units (EPA, 2009b). Panel (b) confirms a sharp post-treatment decline in coal-related emissions in Indiana, consistent with the mandated reduction in coal combustion. Panel (c) shows a moderate increase in natural gas-related emissions, suggesting fuel switching as a compliance strategy. This is in line with the EPA settlement requirement that allowed re-powering of coal units to burn natural gas as an alternative to permanent shutdown. Panel (d) shows that petroleum-related emissions remained relatively flat in both Indiana and the control group throughout the study period. Overall, the results indicate that the observed reduction in total emissions was primarily driven by a targeted decrease in coal use, partially offset by increased reliance on natural gas, with no significant changes in other fuel sources.

Table 2 reports the estimated ATT for Indiana across fuel-specific categories of energy-related CO_2 emissions, using three alternative estimation strategies: SDID, SC, and traditional DID. Consistent with the visual trends presented in Figure 2, the SDID estimates indicate a substantial and statistically significant reduction in both total energy-related emissions (-31.073, $p < 0.1$) and coal-related emissions (-16.080, $p < 0.05$), following the 2011 enforcement action. In contrast, treatment effects for natural gas and petroleum-related emissions are small and not statistically significant, supporting the interpretation that the overall emissions reduction was largely driven by a shift away from coal.

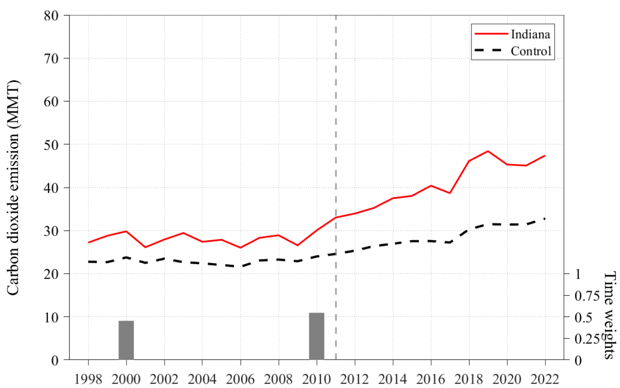
Statistical significance here implies that the estimated effects are unlikely to have arisen by chance under the null hypothesis of no treatment effect (Arkhangelsky et al., 2021; Clarke et al., 2024). The p-values are derived using a placebo-based inference method, in which Indiana's estimated ATT is compared to a distribution of placebo ATTs generated by applying the same SDID procedure to control states. The fact that the actual estimates fall in the tails of this empirical



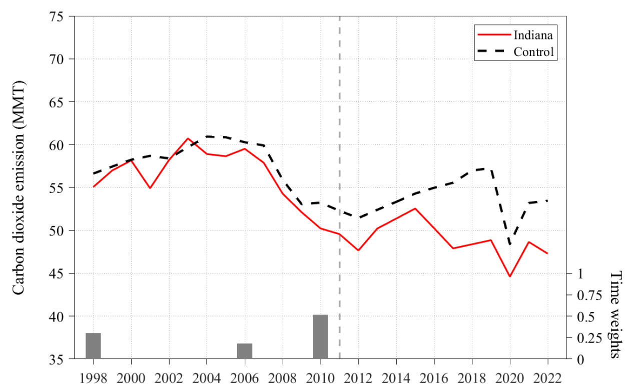
(a) Total energy-related



(b) Coal energy-related



(c) Natural gas energy-related



(d) Petroleum energy-related

Figure 2: Outcome Trends and Time-Specific Weights (fuel specific emission). (a)–(d) show treatment and control comparisons across different outcomes.

distribution strengthens the interpretation of a real treatment effect attributable to the Gallagher settlement.

Notably, SDID yields smaller standard errors relative to the other estimators across all outcome categories, reflecting the estimator's improved precision due to its reweighting mechanism and covariate adjustment. The statistical significance of the SDID estimates—especially for coal-related emissions—corroborates the visual divergence shown in Figure 2 (b), reinforcing the causal interpretation that the Gallagher plant settlement produced a targeted and sustained reduction in coal combustion emissions.

Figure 3 shows the SDID estimates for Indiana and its synthetic control group across five economic sectors: commercial, electric power, industrial, residential, and transportation. Consistent with the fuel-specific patterns reported in Figure 2, the most notable divergence occurs in the electric power sector (Panel b), where Indiana's emissions declined substantially relative to the

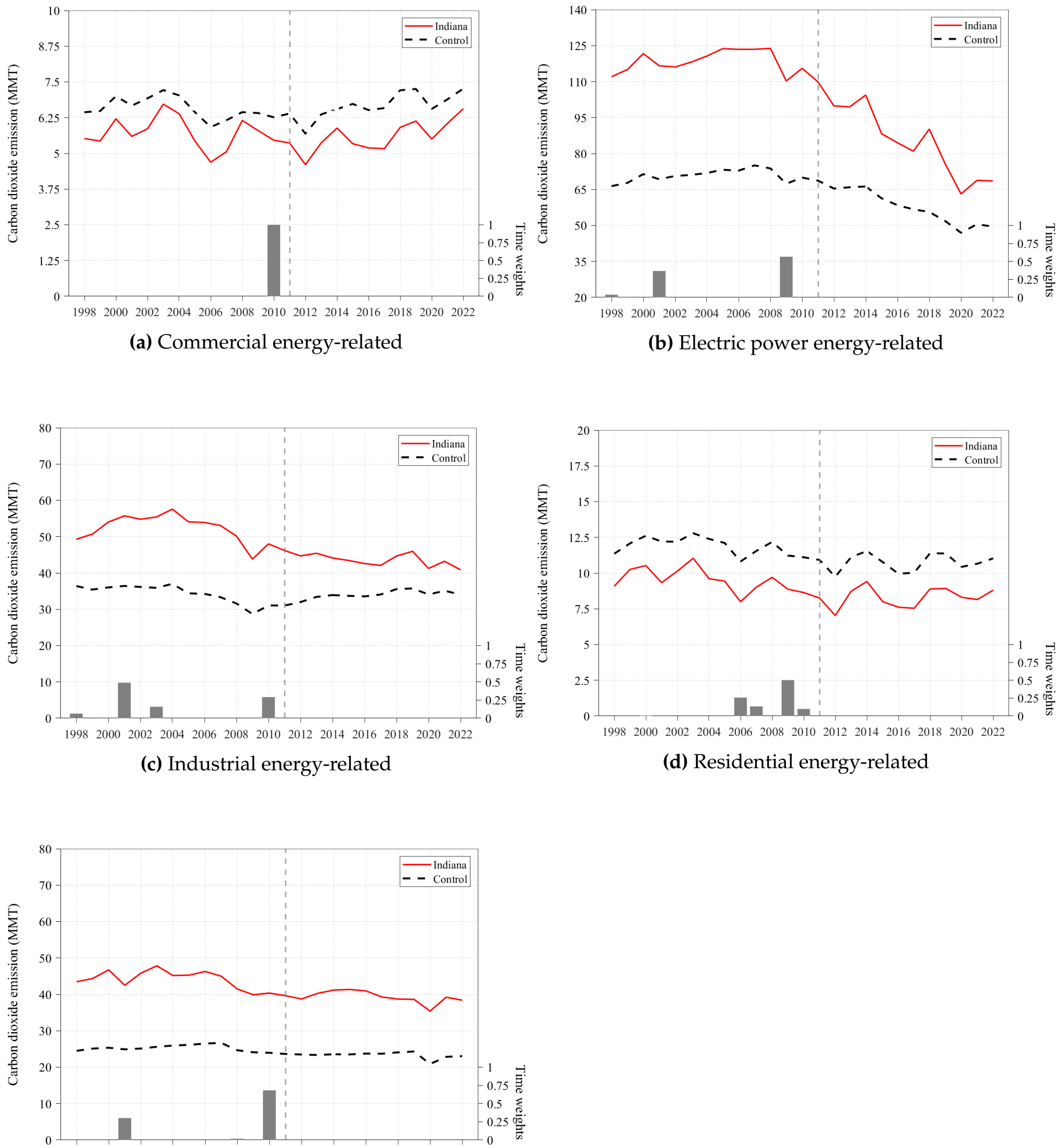
	Synthetic Diff. in Diff		Synthetic Control		Diff. in Diff.	
Total energy-related carbon dioxide emission						
ATT	-31.073*	-23.638	-37.125	-18.864	-39.424***	-38.559***
Standard error	(17.182)	(17.040)	(25.084)	(62.469)	(12.323)	(12.456)
Coal energy-related carbon dioxide emission						
ATT	-16.080**	-10.913**	-20.958*	-12.950	-43.601***	-42.485***
Standard error	(6.861)	(6.828)	(11.698)	(12.054)	(10.270)	(10.529)
Natural gas energy-related carbon dioxide emission						
ATT	6.225	6.022	-4.355	4.823	8.656*	8.521*
Standard error	(5.055)	(6.490)	(12.400)	(21.568)	(4.617)	(4.628)
Petroleum energy-related carbon dioxide emission						
ATT	-2.467	-2.499	-6.292	-3.002	-4.482	-4.595
Standard error	(10.169)	(10.311)	(14.638)	(17.899)	(7.320)	(7.284)
Covariates	✓		✓		✓	
Time FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓			✓	✓

Table 2: Estimates for the fuel-specific average treatment effect on the treated (ATT) on Indiana. We employ the placebo-based standard error estimator. Placebo treatments in estimation is to control units and compute the distribution of placebo estimates $\hat{\tau}_p$ to approximate the sampling variability of the estimator. The variance estimate is given by $\hat{V}_{placebo}(\hat{\tau}) = \text{Var}(\hat{\tau}_p)$, and a $(1-\alpha)$ level confidence interval is contructed as $\hat{\tau} \pm z_{\alpha/2}\sqrt{\hat{V}_{placebo}(\hat{\tau})}$, where $z_{\alpha/2}$ denotes the standard normal critical value (Arkhangelsky et al., 2021; Clarke et al., 2024). Standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

control group following the 2011 intervention. This is expected, given that the Gallagher plant operated as a coal-fired power generator and was subject to the consent decree requiring shutdown or conversion of key units. Panel (c) reveals a statistically meaningful decline in industrial energy-related emissions as well, suggesting that downstream industrial demand may have responded to changes in power generation or related regulatory spillovers.

By contrast, Panels (a), (d), and (e) display relatively parallel trajectories between Indiana and the control group in the commercial, residential, and transportation sectors, with no visible post-treatment divergence. These results underscore that the emissions reductions observed in Indiana were concentrated in the sectors most directly affected by the Gallagher enforcement, particularly electric power, while other sectors remained largely unaffected by the intervention.

Table 3 reports the estimated ATT for Indiana across five economic sectors using SDID, SC, and



(a) Commercial energy-related

(b) Electric power energy-related

(c) Industrial energy-related

(d) Residential energy-related

(e) Transportation energy-related

Figure 3: Outcome Trends and Time-Specific Weights (sectoral specific emission). (a)–(e) show treatment and control comparisons across different outcomes.

traditional DID estimators. The results show that the most pronounced and statistically significant reductions in CO_2 emissions occurred in the electric power (-19.466, $p < 0.01$) and industrial sectors (-9.717, $p < 0.1$) under the SDID specification. These findings are consistent with the visual evidence

	Synthetic Diff. in Diff		Synthetic Control		Diff. in Diff.	
Commercial energy-related carbon dioxide emission						
ATT	-0.207	-0.295	0.571	-0.402	-0.169	-0.267
Standard error	(0.999)	(1.004)	(0.753)	(1.152)	(1.842)	(1.834)
Electric power energy-related carbon dioxide emission						
ATT	-19.466***	-13.436**	-14.690*	-13.661	-26.137***	-25.438***
Standard error	(4.768)	(5.430)	(8.637)	(24.306)	(8.389)	(8.409)
Industrial energy-related carbon dioxide emission						
ATT	-9.717*	-7.944	-10.695	-7.353	-8.595***	-8.225***
Standard error	(5.335)	(6.812)	(12.532)	(29.323)	(3.050)	(3.203)
Residential energy-related carbon dioxide emission						
ATT	0.129	0.023	0.170	-0.187	-0.591	-0.689
Standard error	(0.655)	(0.589)	(2.078)	(1.765)	(0.846)	(0.868)
Transportation energy-related carbon dioxide emission						
ATT	-2.113	0.240	-2.729	0.808	-3.391	-3.940
Standard error	(7.189)	(7.585)	(9.529)	(7.110)	(5.210)	(5.020)
Covariates	✓		✓		✓	
Time FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓			✓	✓

Table 3: Estimates for sectoral-specific average treatment effect on the treated (ATT) on Indiana. We employ the placebo-based standard error estimator. Placebo treatments in estimation is to control units and compute the distribution of placebo estimates $\hat{\tau}_p$ to approximate the sampling variability of the estimator. The variance estimate is given by $\hat{V}_{placebo}(\hat{\tau}) = \text{Var}(\hat{\tau}_p)$, and a $(1-\alpha)$ level confidence interval is contructed as $\hat{\tau} \pm z_{\alpha/2}\sqrt{\hat{V}_{placebo}(\hat{\tau})}$, where $z_{\alpha/2}$ denotes the standard normal critical value (Arkhangelsky et al., 2021; Clarke et al., 2024). Standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

presented in Figure 3, which highlights a clear post-treatment divergence between Indiana and its synthetic control in these two sectors. The electric power sector results reflect the direct regulatory intervention at the Gallagher plant, while the industrial decline may stem from indirect responses to structural changes in electricity generation.

By contrast, the estimated ATT values for the commercial, residential, and transportation sectors are small and statistically insignificant, suggesting that the 2011 intervention had limited impact outside the energy production and industrial domains. Notably, the SDID estimator again yields smaller or comparable standard errors relative to the other two estimators, underscoring its precision advantage. These results collectively suggest that the policy's emissions-reducing effects were concentrated in the sectors most directly tied to coal-based power generation.

This interpretation is further supported by the unit weights ($\hat{\omega}$) reported in Tables B2 and B3. These tables illustrate how the SDID estimator constructs synthetic control units by assigning non-zero weights across a broader and more diverse set of donor states compared to the traditional SC method. In the fuel-specific setting (Table B2), SC often relies on only a handful of states (e.g., Texas or Illinois) with disproportionately large weights, while assigning near zero to most others. By contrast, SDID distributes weights more evenly across relevant donor units such as Mississippi, Pennsylvania, or Arizona—states that better match Indiana's pre-treatment trends in coal and total emissions. A similar pattern is observed in the sectoral-specific setting (Table B3), where SDID assigns meaningful weights to states like California, Georgia, and Illinois across the electric power and industrial sectors, reflecting their greater relevance for constructing a credible counterfactual.

These differences in weight structures highlight the key advantage of SDID: increased flexibly to reweight across both units and time periods while incorporating covariate adjustment to improve the pre-treatment balance. Unlike SC, which requires the treated unit to lie within the convex hull of donor units and thus excludes many potential controls, SDID relaxes this constraint and yields a better approximation of the treated unit's counterfactual trajectory. This richer support helps mitigate sensitivity to outlier units and improves robustness, which in turn explains the consistently smaller standard errors seen in Tables 2 and 3.

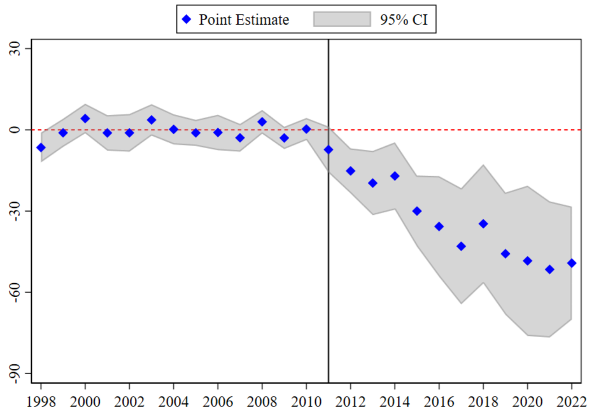
5.2 Event Study Analysis

We estimate dynamic treatment effects using an event study specification based on SDID, following the approach outlined by Clarke et al. (2024). The event-time ATT is computed as the difference between treated and synthetic control series for each year t, normalized by the pre-treatment average. Formally, for each post-treatment year t, we define the event-time ATT as:

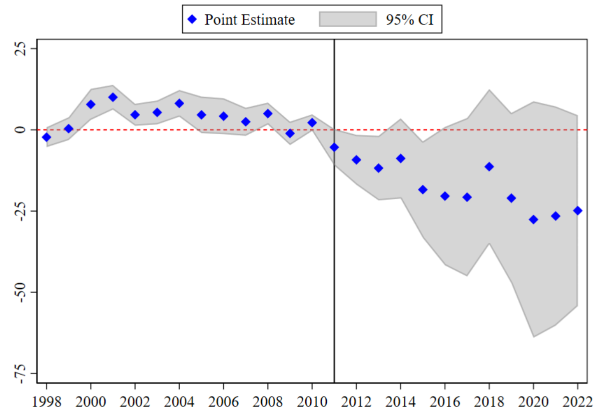
$$\widehat{\delta}_t = \left(Y_t^{\text{treated}} - Y_t^{\text{control}}\right) - \sum_{s<t_0} \lambda_s \left(Y_s^{\text{treated}} - Y_s^{\text{control}}\right), \tag{8}$$

where t_0 is the treatment year, and λ_s are the SDID time weights over the pre-treatment periods. To capture uncertainty in $\widehat{\delta}_t$, we implement clustered bootstrap resampling over units and compute pointwise 95% confidence intervals for each year.

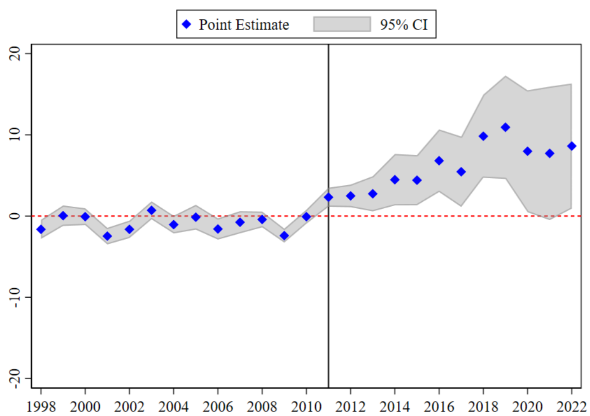
Figure 4 displays the estimated event-time effects across four energy-related outcomes. Panels



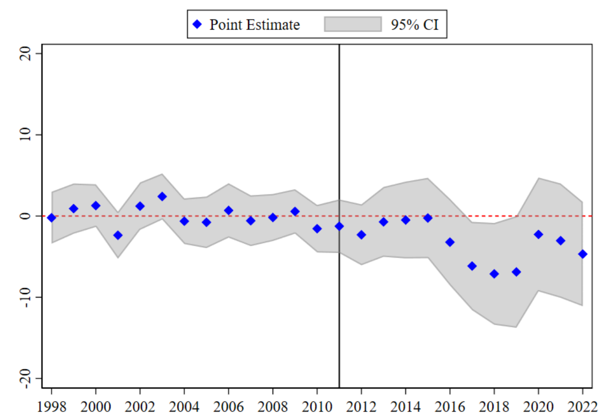
(a) Total energy-related



(b) Coal energy-related



(c) Natural gas energy-related

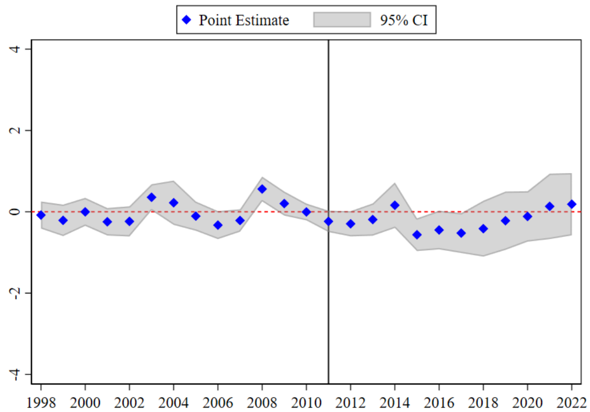


(d) Petroleum energy-related

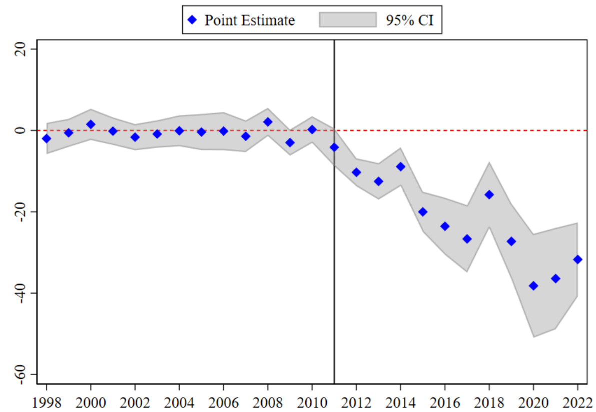
Figure 4: Event Studies (fuel specific emission). (a)–(d) show event studies acorss different outcomes.

(a) and (b) show that total and coal-related CO_2 emissions in Indiana began to diverge sharply from their synthetic control counterparts immediately after the 2011 policy intervention. These declines persist over the post-treatment period and are statistically distinguishable from zero across most years, indicating a sustained treatment effect consistent with the mandated reductions in coal combustion following the Gallagher consent decree.

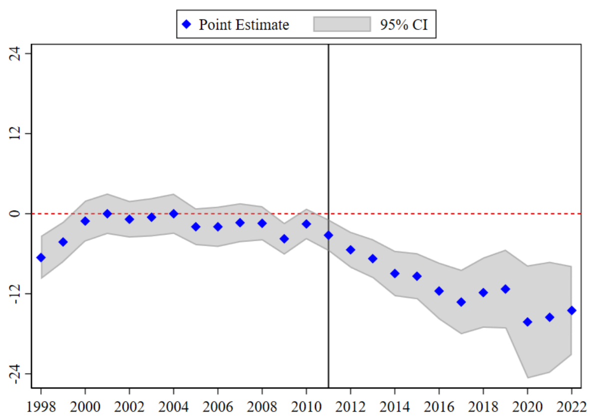
In contrast, Panels (c) and (d) show no significant pre- or post-treatment dynamics for natural gas and petroleum emissions. The point estimates fluctuate around zero, and the 95% confidence bands consistently include the null. These results support the conclusion that the observed reductions in aggregate emissions were primarily driven by the decline in coal use, with little evidence of substitution or spillover effects to other fuel categories.



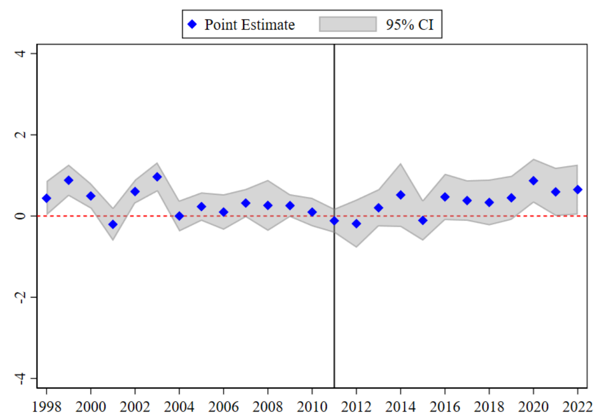
(a) Commercial energy-related



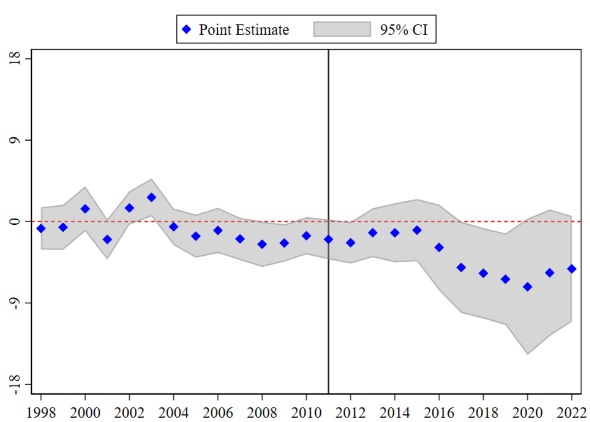
(b) Electric power energy-related



(c) Industrial energy-related



(d) Residential energy-related



(e) Transportation energy-related

Figure 5: Event Studies (sectoral specific emission). (a)–(e) show event studies acorss different outcomes.

Figure 5 presents event study estimates of dynamic treatment effects for Indiana across five economic sectors. Each panel plots the yearly deviation between Indiana and its synthetic control, centered relative to the pre-treatment mean. In line with the results reported in Table 3, the most notable and statistically significant reductions in CO_2 emissions are observed in the electric power (Panel b) and industrial (Panel c) sectors. In these two sectors, the point estimates fall below zero shortly after the 2011 intervention and remain persistently negative, with most estimates statistically different from zero at the 95% confidence level. These patterns suggest a sustained policy effect in sectors directly or indirectly linked to coal-based energy production.

In contrast, the commercial (Panel a), residential (Panel d), and transportation (Panel e) sectors exhibit no statistically significant deviations from the synthetic control group throughout the post-treatment period. Point estimates in these sectors fluctuate narrowly around zero, and the corresponding confidence intervals consistently include the null. These results reinforce the interpretation that the emissions reductions induced by the Gallagher settlement were concentrated within the energy production and industrial use sectors, with little to no spillover into the broader economy.

5.3 Staggered Adoption Analysis

In this section, we broaden our analysis beyond the single-state case to assess whether comparable structural change in coal-fired generation elsewhere produced similar emission reductions. Over the past two decades, multiple states have experienced major coal-unit retirements or fuel conversions, driven by a mix of Clean Air Act-related settlements, state regulatory actions, and economic or operational decisions by utilities. This heterogeneity in both timing and origins of these retirements motivates the use of the staggered adoption SDID framework, which is designed to recover average treatment effects when units undergo analogous transitions at different points in time (Arkhangelsky et al., 2021). Accordingly, we construct a treatment group that includes Indiana as well as 14 additional states (see Appendix B1), each assigned an adoption year corresponding to the first instance in which a significant coal unit was permanently decommissioned.

This staggered treatment timing presents a methodological challenge, as traditional DID and SDID frameworks typically assume a single, uniform treatment onset. To address this, we adapt the SDID estimator to accommodate staggered adoption, following recent extensions by Arkhangelsky et al. (2021) and Clarke et al. (2024). Specifically, we estimate separate treatment effects for each adoption cohort $a \in \mathcal{A}$ by aligning units by their treatment initiation time and constructing synthetic

	without Covariate	with Covariate	Projection Method
Total energy-related carbon dioxide emission			
ATT	-5.208	-5.600	-4.781
Standard error	(3.386)	(3.601)	(3.197)
Coal energy-related carbon dioxide emission			
ATT	-6.195*	-6.546*	-6.227*
Standard error	(3.265)	(3.710)	(3.546)
Electric power energy-related carbon dioxide emission			
ATT	-3.806**	-4.235**	-3.838**
Standard error	(1.703)	(1.848)	(1.780)
Industrial energy-related carbon dioxide emission			
ATT	-1.873**	-2.026**	-1.559**
Standard error	(0.739)	(0.850)	(0.762)
Time FE	✓	✓	✓
State FE	✓	✓	✓

Table 4: Synthetic difference in differences estimates with staggered adoption. Standard errors are clustered at the unit level and computed using bootstrap methods. The third column applies the Kranz-style projection method, which adjusts for covariates by projecting them out based on untreated observations (Kranz, 2022; Clarke et al., 2024). Standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Other fuel and sectoral estimations are in the Appendix Table B6.

controls using pre-treatment periods specific to each group. The overall ATT is then computed as a weighted average of these cohort-specific estimates:

$$\widehat{\text{ATT}} = \sum_{a \in \mathcal{A}} \frac{T^a_{\text{post}}}{T_{\text{post}}} \times \widehat{\tau}_a \tag{9}$$

where T^a_{post} is the number of post-treatment periods for cohort a, and T_{post} is the total number of post-treatment observations across all treated units (Arkhangelsky et al., 2021; Clarke et al., 2024). This approach allows us to flexibly recover a global ATT while respecting the heterogeneity in treatment timing.

Table 4 reports the ATT for this staggered setting across total CO_2 emissions, coal-related emissions, and electric power emissions. We estimate three specifications: one without covariates, one with time-varying covariates (GDP and population growth), and a third using the Kranz-style projection method (Kranz, 2022) to adjust for covariates [6] . The projection method proposed by

[6] $\hat{\tau}_a$ for each cohorts ($a \in \mathcal{A}$) are denoted in Tables B4 and B5.

Kranz (2022) offers an alternative to the residualization approach used in Arkhangelsky et al. (2021) (Clarke et al., 2024). Rather than regressing outcomes on covariates across the entire sample, Kranz suggests first estimating a fixed effects regression of $Y_{it} = X_{it}'\beta + \gamma_t + \mu_i + u_{it}$ using only untreated observations, then projecting out the estimated covariate effects $X_{it}'\hat{\beta}$ from all units. This approach avoids potential bias that may arise when treated units influence the estimation of $\hat{\beta}$, particularly when treatment timing is staggered or correlated with covariate paths.

Our results show that this projection method produces estimates that are consistent with our main findings: significant reductions in coal-related emissions (ATT: -5.891 and -5.839 MMT) and electric power emissions (ATT: -3.523 and -3.564 MMT) across treated states. These effects are statistically significant at conventional levels. Total CO_2 emissions also decline (ATT: -5.394 and -4.895 MMT), though the estimates are less precisely estimated and fall short of significance in some specifications, possibly reflecting heterogeneity in treatment intensity or fuel mix across states.

Overall, this staggered analysis reinforces our earlier results and suggests that coal plant retirements—whether prompted by federal enforcement actions, state-level clean energy or emission mandates, integrated resource planning decisions, or economic pressures such as rising maintenance costs and declining competitiveness of coal- can yield substantial and measurable reductions in energy-related CO_2 emissions, particularly in the power generation sector. Moreover, the comparison between residualization and projection methods highlights the importance of careful covariate adjustment when using SDID in the presence of treatment heterogeneity.

6 Valuation of Environmental Consumer Surplus

The preceding staggered adoption analysis highlights significant and sustained reductions in carbon emissions resulting from regulatory enforcement at coal-fired power plants. To complement these findings and provide comprehensive insights for policymakers, this section conducts a detailed welfare analysis quantifying the ECS. By estimating the economic value of reduced emissions through avoided climate damages, we capture a broader scope of societal benefits beyond the immediate emission reductions documented in the preceding analysis.

Environmental consumer surplus represents the economic welfare gained by society from improvements in environmental quality, specifically reductions in carbon emissions. Following widely accepted practices in environmental and climate economics, ECS is defined as the aggregate societal benefit obtained by integrating the marginal damage (MD) function over the range of emissions reductions achieved (Greenstone and Jack, 2015; Auffhammer, 2018):

$$\text{ECS} = \int_{E_{\text{pre}}}^{E_{\text{post}}} MD(E)\, dE \tag{10}$$

Here, E^{pre} and E^{post} denote emission levels before and after policy enforcement, respectively, while $MD(E)$ captures the incremental societal damages resulting from each additional unit of emissions. Marginal damages reflect the monetized value of negative externalities, including climate-related losses such as increased severity of weather extremes, human health effects, ecological degradation, and agricultural impacts.

Given the global and long-term nature of carbon externalities, estimating a precise marginal damage curve is empirically challenging. Accordingly, a widely accepted approach in both academic and policy contexts is to use the SCC as a proxy for marginal damage. The SCC represents the present value of monetized damages from an incremental ton of CO_2 emissions, incorporating uncertainty about future climate responses, economic growth trajectories, and discounting parameters (Nordhaus, 2017; House, 2021; Rennert et al., 2022).

Following the guidance of the Interagency Working Group on Social Cost of Greenhouse Gases, we adopt the central SCC estimate of \$51 per ton of CO_2, adjusted to 2020 dollars (House, 2021). Treating SCC as constant over the observed range of emission reductions enables a tractable yet policy-relevant estimation of annual ECS for each treated unit a:

$$\text{ECS}_a^{\text{annual}} = -\hat{\tau}_a \times 10^6 \text{ tons/MMT} \times \$51/\text{ton} \tag{11}$$

This expression yields the annual monetized climate benefit attributable to the reduction in energy-related CO_2 emissions for unit a. [7] Recognizing the temporal dimension of policy benefits, we extend the analysis by computing the present discounted value of these benefits over a fixed time horizon. Specifically, we evaluate the cumulative ECS for each treated unit using a standard 3% social discount rate over a 10-year post-treatment window, consistent with economic evaluation principles in climate policy (Goulder and WILLIAMS III, 2012; Rennert et al., 2022). The resulting expression accounts for the share of post-treatment years observed for each unit relative to the full

[7] These estimates reflect only the monetized climate benefits from reduced CO_2 emissions. They do not include any costs or opportunity costs associated with plant retirement, including potential compliance expenditures borne or economic impacts on the surrounding community.

	Indiana (SDID)		U.S. (Staggered-SDID)	
Total energy-related carbon dioxide emission				
	15.77	[-1.32, 32.87]		
Coal energy-related carbon dioxide emission				
	8.16	[1.34, 14.99]	3.32	[-0.37, 7.01]
Electric power energy-related carbon dioxide emission				
	9.88	[5.14, 14.63]	2.15	[0.31, 3.99]
Industrial energy-related carbon dioxide emission				
	4.93	[-0.38, 10.24]	1.03	[0.18, 1.87]
			(Unit: billion USD)	

Table 5: Cumulative environmental consumer surplus (NPV) over the treatment. For Indiana, ECS values are derived from the SDID estimates with covariates. For the U.S., ECS values are computed using the SDID with a staggered adoption. We omit the national total ECS estimate, as the aggregate emission reduction effect was not statistically significant in the corresponding estimates (see Table 4). Bracketed values report the 95% confidence interval for ECS total, obtained through the transformation: $\text{ECS}^{\text{annual}}_{a,CI} = -\hat{\tau}_{a,CI} \times 10^6 \times \$51/\text{ton}$, to the SDID estimate evaluated at $\hat{\tau}_{a,CI} = \hat{\tau}_a \pm 1.96\, SE$. All monetary values are in 2020 billion USD.

post-period:

$$\text{ECS}^{\text{total}}_a = \sum_{a \in \mathcal{A}} \frac{T^a_{\text{post}}}{T_{\text{post}}} \sum_{t=T_{\text{pre}}+1}^{T} \frac{\text{ECS}^{\text{annual}}_a}{(1+0.03)^{t-T_{\text{pre}}}} \tag{12}$$

This formulation flexibly accommodates staggered treatment timing across units by proportionally weighting each treated unit's contribution based on its observed exposure to the post-policy period. It allows us to aggregate the net present value of environmental welfare gains across heterogeneous adoption timelines [8].

Table 5 summarizes the estimated cumulative environmental consumer surplus for Indiana and the U.S., using the SDID estimates with covariates and the staggered-SDID approach, respectively. For Indiana, we estimate a total ECS of \$15.77 billion over the treatment horizon, driven primarily by reductions in emissions from coal and industrial sectors. In the U.S.-wide staggered setting, we provide sector-specific ECS estimates for the coal and industrial categories, which exhibit statistically significant reductions in emissions. However, we do not report a national total ECS value, as the aggregate post-treatment effect on total emissions was not statistically distinguishable

[8] When considering a single treated unit (i.e., $a = 1$), the expression simplifies as $\hat{\tau}_a = \hat{\tau}$ and $T^a_{\text{post}} = T_{\text{post}}$, reducing the cumulative ECS calculation to $\text{ECS}^{\text{total}} = \sum_{t=T_{\text{pre}}+1}^{T_{\text{post}}} \text{ECS}^{\text{annual}}/(1+0.03)^{t-T_{\text{pre}}}$.

from zero in the staggered-SDID analysis (see Table 4).

Taken together, these welfare estimates underscore the substantial economic value of emission reductions achieved through regulatory enforcement. Beyond documenting statistically significant decreases in carbon emissions, this analysis provides a monetary valuation of the associated climate benefits, reinforcing the broader societal importance of such environmental regulations. By incorporating staggered adoption dynamics and formally monetizing avoided climate damages, this section complements the emission reduction findings and offers a more holistic picture of policy effectiveness from a welfare economics perspective.

7 Discussion and Conclusion

This study evaluates the effectiveness of environmental enforcement actions in reducing carbon dioxide emissions, using the 2009 consent decree at Duke Energy's Gallagher coal plant as a quasi-experimental case. Utilizing the SDID estimator of Arkhangelsky et al. (2021), we identify significant and persistent reductions in both total and coal-specific carbon emissions at the state level. Our results confirm that legally mandated fuel switching and plant retirements can yield substantial emissions reductions, particularly within historically coal-dependent electric power sectors.

Specifically, the Gallagher consent decree resulted in an approximately 16 MMT reduction in coal-related emissions and a nearly 20 MMT reduction in emissions from the electric power sector in Indiana. These outcomes highlight the effectiveness of targeted regulatory interventions under the Clean Air Act, not only in addressing local air pollution but also in achieving meaningful climate-related benefits. The concentration of observed emission reductions within sectors directly affected by the enforcement actions further underscores the precision and efficacy of regulatory mandates in inducing significant structural changes in emissions-intensive sectors.

To assess the broader applicability and generalizability of our findings, we expanded the analysis to a staggered adoption setting involving 14 additional states that experienced similar coal unit retirements. The staggered SDID framework reveals consistent emission declines across these states, reinforcing the robustness of our main findings. Importantly, methodological insights from our study demonstrate that the projection-based covariate adjustment method introduced by Kranz (2022) significantly enhances estimation precision compared to conventional residualization, particularly in staggered adoption contexts. This methodological contribution provides valuable guidance for empirical researchers examining heterogeneous environmental policy interventions.

The welfare implications of our analysis further deepen the policy relevance of these findings. By calculating the ECS using a standardized SCC, we translate the emissions reductions into monetary terms, estimating cumulative societal benefits of approximately $15.77 billion for Indiana over a ten-year policy horizon. Additionally, in the staggered adoption scenario across multiple states, we observe meaningful sector-specific welfare gains totaling approximately $3.94 billion and $2.11 billion for coal-related and electric power emissions, respectively. These welfare estimates offer critical insights for policymakers by quantifying the economic value of regulatory enforcement beyond mere emissions reductions, emphasizing the substantial climate benefits achievable through targeted legal mandates.

Our results hold significant implications for climate policy formulation. Regulatory enforcement actions, such as mandated shutdowns or repowering of legacy coal infrastructure, can complement market-based instruments like carbon pricing schemes by delivering immediate, targeted, and substantial emissions reductions. These regulatory strategies are particularly relevant as policymakers strive toward ambitious net-zero emissions targets. By clearly demonstrating the effectiveness and economic benefits of enforcement-based policy tools, our findings provide actionable evidence that such interventions should play a central role in comprehensive climate strategies.

Future research avenues remain promising, including investigating firm-level compliance costs associated with enforcement actions, analyzing the impacts on electricity market dynamics, and evaluating public health outcomes due to reduced local air pollutants. Moreover, leveraging satellite-based pollution monitoring data and incorporating granular air quality metrics could provide additional insights into the environmental co-benefits of regulatory actions. By examining these dimensions, researchers can further elucidate the broader societal and economic implications of targeted environmental enforcement.

In conclusion, our analysis robustly demonstrates that regulatory enforcement under the Clean Air Act not only significantly curbs emissions but also delivers substantial economic welfare gains through reduced climate damages. These insights underscore the integral role enforcement-based interventions can play in achieving ambitious climate goals, offering policymakers clear pathways to accelerate the transition toward sustainable energy systems.

References

ABADIE, A., A. DIAMOND, AND J. HAINMUELLER (2010): "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American Statistical Association*, 105, 493–505.

ALDY, J. E. AND W. A. PIZER (2015): "The competitiveness impacts of climate change mitigation policies," *Journal of the Association of Environmental and Resource Economists*, 2, 565–595.

ANG, J. B. (2007): "CO2 emissions, energy consumption, and output in France," *Energy policy*, 35, 4772–4778.

ARKHANGELSKY, D., S. ATHEY, D. A. HIRSHBERG, G. W. IMBENS, AND S. WAGER (2021): "Synthetic difference-in-differences," *American Economic Review*, 111, 4088–4118.

AUFFHAMMER, M. (2018): "Quantifying economic damages from climate change," *Journal of Economic Perspectives*, 32, 33–52.

BISTLINE, J., A. BERGMAN, G. BLANFORD, M. BROWN, D. BURTRAW, M. DOMESHEK, A. FAWCETT, A. HAMILTON, G. IYER, J. JENKINS, ET AL. (2025): "Impacts of EPA's finalized power plant greenhouse gas standards," *Science*, 387, 140–143.

BURTRAW, D. AND M. WOERMAN (2013): "Technology flexibility and stringency for greenhouse gas regulations," *Resources for the Future DP*, 13–24.

CAI, Y. AND T. S. LONTZEK (2019): "The social cost of carbon with economic and climate risks," *Journal of Political Economy*, 127, 2684–2734.

CALLAWAY, B. AND P. H. SANT'ANNA (2021): "Difference-in-differences with multiple time periods," *Journal of econometrics*, 225, 200–230.

CAMPOS MORALES, C., E. L. PAKHTIGIAN, J. R. LANDRY, H. WISEMAN, A. T. PHAM, AND W. PENG (2024): "Designing retirement strategies for coal-fired power plants to mitigate air pollution and health impacts," *Environmental Science & Technology*, 58, 15371–15380.

CLARKE, D., D. PAILAÑIR, S. ATHEY, AND G. IMBENS (2024): "On synthetic difference-in-differences and related estimation methods in Stata," *The Stata Journal*, 24, 557–598.

CONGRESSIONAL BUDGET OFFICE (2023): "CO_2 Emissions in the Electric Power Sector," Tech. Rep. 58419, Congressional Budget Office, cBO Publication 58419.

CULLEN, J. (2013): "Measuring the environmental benefits of wind-generated electricity," *American Economic Journal: Economic Policy*, 5, 107–133.

CUMMISKEY, K., C. KIM, C. CHOIRAT, L. R. HENNEMAN, J. SCHWARTZ, AND C. ZIGLER (2019): "A source-oriented approach to coal power plant emissions health effects," *arXiv preprint arXiv:1902.09703*.

DAVIS, S. J. AND R. H. SOCOLOW (2014): "Commitment accounting of CO2 emissions," *Environmental Research Letters*, 9, 084018.

DIETZ, T. AND E. A. ROSA (1997): "Effects of population and affluence on CO2 emissions," *Proceedings of the national academy of sciences*, 94, 175–179.

EPA (2009a): "Consent Decree: United States v. Duke Energy Indiana, Inc." .

——— (2009b): "Duke Energy Gallagher Plant Clean Air Act Settlement," .

——— (2023): "Coal-Fired Power Plant Enforcement," .

FEDERAL RESERVE BANK OF ST. LOUIS (2024): "Annual Population Estimates by State," Accessed: 2025-05-28.

FILONCHYK, M. AND M. P. PETERSON (2023): "An integrated analysis of air pollution from US coal-fired power plants," *Geoscience Frontiers*, 14, 101498.

FOWLIE, M. AND N. MULLER (2019): "Market-based emissions regulation when damages vary across sources: What are the gains from differentiation?" *Journal of the Association of Environmental and Resource Economists*, 6, 593–632.

GATHRID, S., J. WAYLAND, S. WAYLAND, R. DESHMUKH, AND G. C. WU (2025): "Strategies to accelerate US coal power phase-out using contextual retirement vulnerabilities," *Nature Energy*, 10, 1274–1288.

GILLINGHAM, K. AND J. H. STOCK (2018): "The cost of reducing greenhouse gas emissions," *Journal of Economic Perspectives*, 32, 53–72.

GOULDER, L. H. AND R. C. WILLIAMS III (2012): "The choice of discount rate for climate change policy evaluation," *Climate Change Economics*, 3, 1250024.

GRAFF ZIVIN, J. AND M. NEIDELL (2013): "Environment, health, and human capital," *Journal of economic literature*, 51, 689–730.

GREENSTONE, M. AND R. HANNA (2014): "Environmental regulations, air and water pollution, and infant mortality in India," *American Economic Review*, 104, 3038–3072.

GREENSTONE, M. AND B. K. JACK (2015): "Envirodevonomics: A research agenda for an emerging field," *Journal of Economic Literature*, 53, 5–42.

HOUSE, W. (2021): "Social cost of carbon, methane, and nitrous oxide-interim estimates under executive order 13990," *Technical support document, Interagency Working Group on Social Cost of Greenhouse Gases, United States Government., Washington DC, USA*.

HUNTINGTON, H. AND B. LIDDLE (2022): "How energy prices shape OECD economic growth: Panel evidence from multiple decades," *Energy Economics*, 111, 106082.

KRANZ, S. (2022): "Synthetic difference-in-differences with time-varying covariates," *arXiv preprint arXiv:2202.02903*.

MURRAY, B. C. AND P. T. MANILOFF (2015): "Why have greenhouse emissions in RGGI states declined? An econometric attribution to economic, energy market, and policy factors," *Energy Economics*, 51, 581–589.

NET, I. (2021): "Zero by 2050: a roadmap for the global energy sector," *Int Energ y Agency*, 224.

NORDHAUS, W. D. (2017): "Revisiting the social cost of carbon," *Proceedings of the National Academy of Sciences*, 114, 1518–1523.

O'NEILL, B. C., B. LIDDLE, L. JIANG, K. R. SMITH, S. PACHAURI, M. DALTON, AND R. FUCHS (2012): "Demographic change and carbon dioxide emissions," *The Lancet*, 380, 157–164.

PREST, B. C., H. FELL, D. GORDON, AND T. CONWAY (2024): "Estimating the emissions reductions from supply-side fossil fuel interventions," *Energy Economics*, 136, 107720.

RENNERT, K., F. ERRICKSON, B. C. PREST, L. RENNELS, R. G. NEWELL, W. PIZER, C. KINGDON,

J. WINGENROTH, R. COOKE, B. PARTHUM, ET AL. (2022): "Comprehensive evidence implies a higher social cost of CO2," *Nature*, 610, 687–692.

SAMPEDRO, J., R. Y. CUI, H. MCJEON, S. J. SMITH, N. HULTMAN, L. HE, A. SEN, R. VAN DINGENEN, AND I. CAZCARRO (2021): "Quantifying the reductions in mortality from air-pollution by cancelling new coal power plants," *Energy and Climate Change*, 2, 100023.

SGARCIU, S., D. SCHOLZ, AND F. MÜSGENS (2023): "How CO2 prices accelerate decarbonisation–The case of coal-fired generation in Germany," *Energy Policy*, 173, 113375.

SHI, A. (2003): "The impact of population pressure on global carbon dioxide emissions, 1975–1996: evidence from pooled cross-country data," *Ecological economics*, 44, 29–42.

STERN, D. I. (2004): "The rise and fall of the environmental Kuznets curve," *World development*, 32, 1419–1439.

STRASERT, B., S. C. TEH, AND D. S. COHAN (2019): "Air quality and health benefits from potential coal power plant closures in Texas," *Journal of the Air & Waste Management Association*, 69, 333–350.

SUN, L. AND S. ABRAHAM (2021): "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of econometrics*, 225, 175–199.

U.S. BEA (2025): "Regional Data: GDP and Personal Income by State," Accessed: 2025-05-28.

U.S. ENERGY INFORMATION ADMINISTRATION (2023): "Documentation for Estimates of State Energy-Related Carbon Dioxide Emissions," Tech. rep., U.S. Department of Energy, retrieved from internal documentation.

——— (2024): "State Energy-Related Carbon Dioxide Emissions by Year," https://www.eia.gov/environment/emissions/state/, accessed June 2025.

——— (2025): "Coal Data Browser: Total Coal Consumption – Electric Power Sector (2000–2024)," https://www.eia.gov/coal/data/browser/, accessed: 3 September 2025.

U.S. SEC. (2009): "Form 10-K Annual Report for the Fiscal Year Ended December 31, 2008," https://www.sec.gov/Archives/edgar/data/1326160/000119312509041096/d10k.htm, filed with the U.S. Securities and Exchange Commission.

WISEMAN, H. J. (2022): "Regional Cooperative Federalism and the US Electric Grid," *Geo. Wash. L. Rev.*, 90, 147.

Appendix

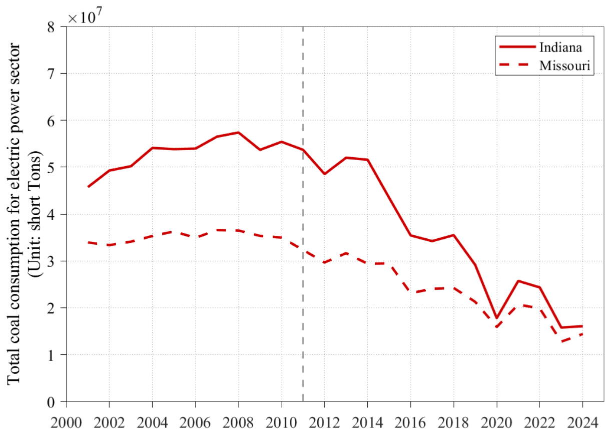
A Linkage Considerations with MISO States

A central concern in empirical evaluations of environmental regulation is the potential for treatment effects to extend beyond the directly affected jurisdiction. In our study, Indiana constitutes the focal treatment state due to the 2009 Gallagher Clean Air Act consent decree, which triggered substantial operational changes beginning in 2011. While our primary specification excludes states listed in Table B1 that experienced similar enforcement actions, one might reasonably question whether Indiana's membership in the Midcontinent Independent System Operator (MISO) introduces spillover channels to other states in the network. The purpose of this appendix is to examine these potential linkages and to clarify why MISO states that were not directly treated remain valid members of the control sample in our analysis.

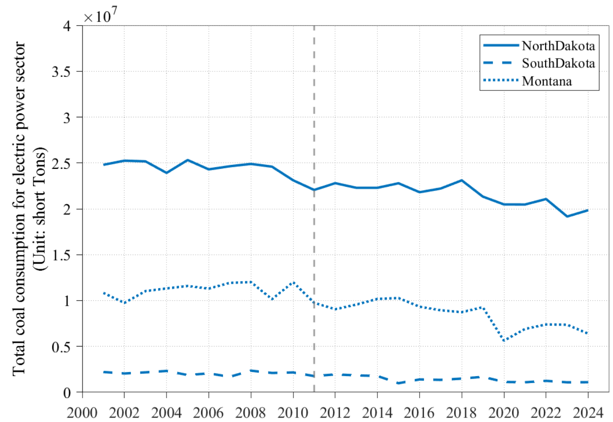
MISO is a regional transmission organization (RTO) responsible for coordinating electricity generation and transmission across a large set of U.S. states. Because electricity markets within an RTO are integrated, shocks in one state—such as plant retirements, regulatory compliance costs, or changes in fuel mix—can, in principle, affect generation and dispatch decisions in neighboring states (Burtraw and Woerman, 2013; Gillingham and Stock, 2018; Wiseman, 2022). This interdependence could translate into indirect changes in coal consumption and related emissions, even if those states were not directly targeted by Clean Air Act enforcement actions.

Consequently, a valid empirical design requires considering whether Indiana's regulatory shock may have altered emissions in other MISO states. If significant spillovers were present, including such states in the control group would bias estimates of Indiana's treatment effect by contaminating the counterfactual comparison (Abadie et al., 2010). On the other hand, if spillovers are minimal or statistically undetectable, maintaining these states in the control group enhances sample size and improves precision without compromising identification.

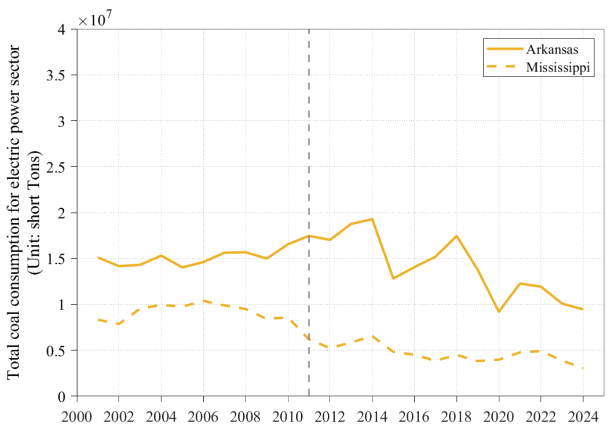
To evaluate linkage effects, we identified MISO states that were not already removed from the sample due to direct treatment events documented in Table B1. This yielded a set of states across three MISO sub-regions: Central MISO (Illinois and Missouri), North MISO (North Dakota, South Dakota, and Montana), South MISO (Arkansas and Mississippi). These states share transmission ties with Indiana but did not experience comparable Clean Air Act settlements during the study period. They thus represent plausible candidates for testing potential spillover effects.



(a) Central MISO



(b) North MISO



(c) South MISO

Figure A1: Annual Coal Consumption in the Electric Power Sector Across MISO Regions (2001–2024). This figure shows annual coal consumption for the electric power sector in selected MISO states, grouped by region (Central, North, and South). Data are drawn from the U.S. Energy Information Administration's Coal Data Browser (Total Coal Consumption: Electric Power Sector) (U.S. Energy Information Administration, 2025). Units are short tons.

We began by examining trends in annual coal consumption for the electric power sector in these states. Figure A1 presents the trajectories from 2001 to 2024, grouped by MISO sub-region. A vertical line marks Indiana's 2011 treatment year.

The descriptive evidence shows no pronounced discontinuities in neighboring states' coal consumption around 2011. Central MISO states (Illinois and Missouri) display gradual declines consistent with national trends toward reduced coal use (Sampedro et al., 2021). North MISO states (North Dakota, South Dakota, and Montana) exhibit relatively stable or gently declining patterns, while South MISO states (Arkansas and Mississippi) show some year-to-year volatility without a clear structural break. If Indiana's enforcement had displaced generation or altered regional coal

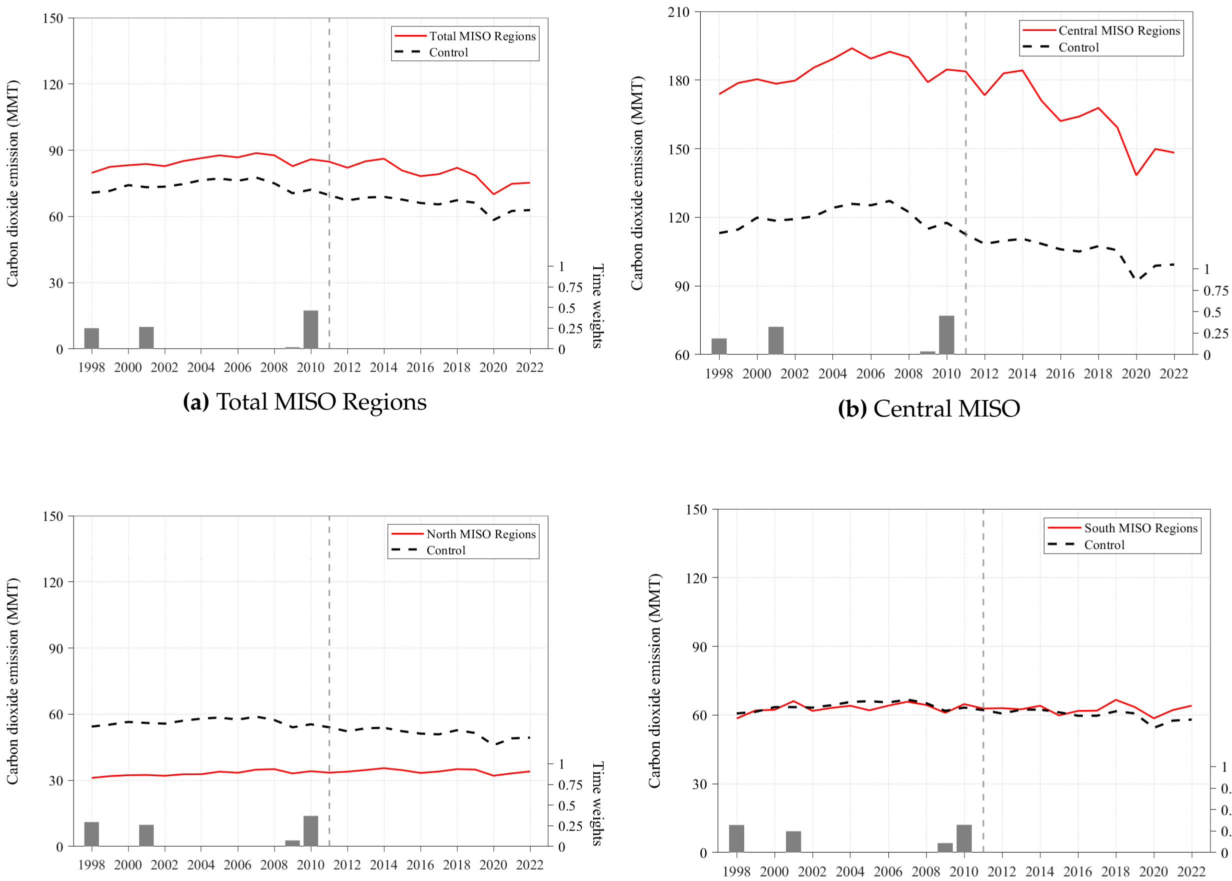
	Total MISO Regions		Central MISO		North MISO		South MISO	
Total energy-related carbon dioxide emission								
ATT	1.440	2.026	-2.874	-5.254	3.523	5.019	3.437	3.418
Standard error	(6.360)	(6.391)	(11.178)	(11.119)	(9.131)	(9.131)	(9.719)	(10.132)
Coal energy-related carbon dioxide emission								
ATT	0.028	0.128	-3.133	-3.629	2.398	2.466	2.094	2.144
Standard error	(3.882)	(3.687)	(6.735)	(6.570)	(4.673)	(4.212)	(5.646)	(5.158)
Natural gas energy-related carbon dioxide emission								
ATT	-0.742	-0.711	-1.641	-1.674	-1.255	-1.179	0.726	0.774
Standard error	(3.500)	(3.374)	(5.217)	(5.165)	(4.095)	(3.999)	(4.908)	(4.726)
Petroleum energy-related carbon dioxide emission								
ATT	0.768	0.621	-1.020	-1.372	2.061	2.156	-0.489	-0.589
Standard error	(4.309)	(4.295)	(7.234)	(7.446)	(5.606)	(5.591)	(6.460)	(6.454)
Covariates	✓		✓		✓		✓	
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓

Table A1: Synthetic difference in differences estimates of energy-related carbon dioxide emissions across MISO regions following Indiana's treatment year. We employ the placebo-based standard error estimator. Placebo treatments in estimation is to control units and compute the distribution of placebo estimates $\hat{\tau}_p$ to approximate the sampling variability of the estimator. The variance estimate is given by $\hat{V}_{placebo}(\hat{\tau}) = \text{Var}(\hat{\tau}_p)$, and a $(1-\alpha)$ level confidence interval is contructed as $\hat{\tau} \pm z_{\alpha/2}\sqrt{\hat{V}_{placebo}(\hat{\tau})}$, where $z_{\alpha/2}$ denotes the standard normal critical value (Arkhangelsky et al., 2021; Clarke et al., 2024). Standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

procurement significantly, we would expect visible changes in these trajectories. The absence of such patterns provides an initial indication that spillover effects were weak.

To formally test for spillovers, we applied the SDID estimator (Arkhangelsky et al., 2021; Clarke et al., 2024) to assess whether Indiana's treatment had measurable impacts on emissions in these MISO states. Table A1 reports the estimated ATTs for total energy-related CO_2 emissions and fuel-specific emissions (coal, natural gas, petroleum) across the aggregate MISO sample and each sub-region. Standard errors were derived using placebo-based inference, which generates an empirical null distribution by applying the same procedure to untreated states.

Across all specifications, the estimated spillover effects are small and statistically indistinguishable from zero. For instance, total CO_2 emissions in Central MISO states display ATT estimates



(a) Total MISO Regions

(b) Central MISO

(c) North MISO

(d) South Regions

Figure A2: Carbon dioxide emissions in the electric power sector for MISO regions and control states.

ranging from -2.874 to -5.254 million short tons, but standard errors are substantially larger, rendering the effects insignificant. North and South MISO results show positive ATT values in some cases, yet again with wide confidence intervals. No consistent or significant patterns emerge across fuels or regions. These null findings corroborate the descriptive evidence: Indiana's Gallagher settlement did not generate detectable spillover effects on emissions in other MISO states.

Figure A2 complements these results by plotting the SDID trajectories of carbon dioxide emissions for MISO regions relative to their synthetic controls. The figure shows that, although Indiana's Gallagher settlement marked a sharp shift in Indiana, neighboring MISO regions exhibit no statistically discernible spillover effects, reinforcing their suitability as control states in the main analysis

The absence of significant linkage effects may be explained by several factors. First, while MISO coordinates regional markets, transmission constraints and localized generation costs often limit the extent of cross-state substitution (Cullen, 2013; Fowlie and Muller, 2019). Indiana's Gallagher settlement, although impactful within the state, may not have been large enough to alter dispatch across state borders. Second, compliance adjustments likely occurred through intra-state mechanisms. Duke Energy may have reallocated generation within Indiana, repowering existing units with natural gas rather than shifting production to external states. This would localize the policy shock, minimizing regional spillovers (Prest et al., 2024). Third, broader structural trends in U.S. coal markets during the 2010s—including declining natural gas prices and growth in renewables—already exerted downward pressure on coal consumption nationwide (Net, 2021). Against this backdrop, any incremental spillover effects from Indiana's enforcement would be difficult to detect statistically.

These results have two key implications. First, they suggest that Indiana's treatment effect is unlikely to have been confounded by indirect MISO spillovers. Thus, retaining these states in the control group is appropriate and improves estimation precision without compromising validity. Second, the exercise strengthens the transparency of our empirical strategy. By explicitly documenting why potential linkage concerns do not undermine our identification, we reassure readers that our results are not driven by unaccounted-for regional dynamics.

This approach aligns with best practices in applied econometrics, which emphasize testing for potential contamination of control units in settings where spillovers are plausible (Sun and Abraham, 2021). Both descriptive evidence and SDID estimates point to weak or nonexistent spillover effects. Accordingly, these states remain part of the control sample in the main analysis. This exercise reinforces the robustness of our causal findings and highlights the importance of considering grid-level linkages in environmental policy evaluation.

B Additional Figures and Tables

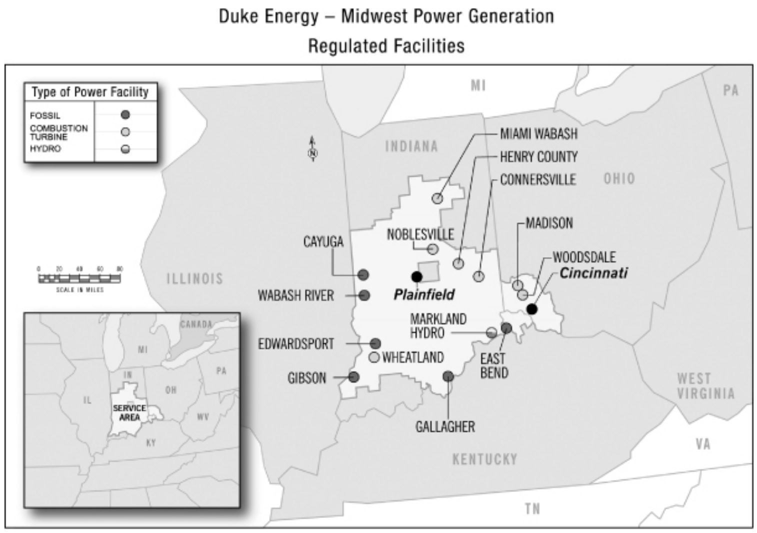


Figure B1: Geographic Distribution of Duke Energy's Regulated Power Generation Facilities in Indiana. Source: Form 10-K (2008), U.S. Securities and Exchange Comission. U.S. SEC. (2009)

State	Year	Coal-Fired Power Plant Settlement
Alabama	2013	Tennessee Valley Authority Clean Air Act Settlement
Florida	2000	Tampa Electric Company (TECO) Clean Air Act (CAA) Settlement
Iowa	2015	Interstate Power and Light Company Clean Air Act Settlement
Kentucky	2017	Tennessee Valley Authority Clean Air Act Settlement
Louisiana	2012	Louisiana Generating Settlement
Michigan	2016	Consumers Energy Clean Air Act Settlement
Minnesota	2015	Minnesota Power Settlement
New Jersey	2007	PSEG Fossil L.L.C. Settlement
New Mexico	2015	Four Corners Power Plant Clean Air Act Settlement
North Carolina	2015	Duke Energy Corporation Clean Air Act Settlement
Ohio	2012	American Municipal Power Clean Air Act Settlement
Tennessee	2012	Tennessee Valley Authority Clean Air Act Settlement
Virginia	2003	Virginia Electric and Power Company Clean Air Act Settlement
Wisconsin	2003	Wisconsin Electric Power Company Clean Air Act Civil Settlement

Table B1: List of 14 Treated States in Staggered Adoption Analysis and Their Treatment Onset Years This table lists the 14 U.S. states included in the staggered adoption analysis. The year indicates the first recorded coal-fired unit retirement or refueling associated with a Clean Air Act enforcement settlement. Settlement information is sourced from the U.S. Environmental Protection Agency's Coal-Fired Power Plant Enforcement records EPA (2023).

	Total		Coal		Natural gas		Petroleum	
	SDID	SC	SDID	SC	SDID	SC	SDID	SC
Alaska	0.0371	0.0019	0.00003	0	0.0380	0.0005	0.0185	0.00003
Arizona	0.1927	0.0019	0.00003	0	0.0144	0.0005	0.0104	0.2594
Arkansas	0.0003	0.0019	0.00003	0	0.0341	0.0005	0.0249	0.00003
California	0.0625	0.0019	0.00003	0	0.0015	0.0005	0.0441	0.00003
Colorado	0.0206	0.0025	0.0055	0	0.0015	0.0005	0.0036	0.0015
Connecticut	0.0003	0.0121	0.00003	0	0.0290	0.0005	0.0465	0.00003
Delaware	0.0003	0.0019	0.00003	0	0.0290	0.0005	0.0309	0.00003
District of Columbia	0.0003	0.0019	0.00003	0	0.0293	0.0005	0.0291	0.00003
Georgia	0.0421	0.0019	0.0736	0	0.0365	0.1828	0.0080	0.00003
Hawaii	0.0003	0.0019	0.00003	0	0.0262	0.0005	0.0201	0.00003
Idaho	0.0133	0.0371	0.00003	0	0.0235	0.0005	0.0209	0.1034
Illinois	0.1043	0.3395	0.0642	0	0.0619	0.1461	0.0050	0.00003
Kansas	0.0703	0.2203	0.1228	0	0.0258	0.0005	0.0421	0.4049
Maine	0.0230	0.0019	0.00003	0	0.0050	0.0005	0.0546	0.00003
Maryland	0.0269	0.0019	0.0245	0	0.0412	0.0080	0.0289	0.0020
Massachusetts	0.0163	0.0019	0.00003	0	0.0412	0.0005	0.0484	0.0002
Mississippi	0.3119	0.1378	0.1091	0	0.0197	0.0005	0.0330	0.00003
Missouri	0.0203	0.0019	0.00003	0	0.0299	0.0005	0.0351	0.00003
Montana	0.0005	0.0193	0.00003	0	0.0266	0.0005	0.0206	0.00009
Nebraska	0.0003	0.0019	0.00003	0	0.0239	0.0005	0.0236	0.00003
Nevada	0.0003	0.0019	0.00003	0	0.0227	0.0005	0.0036	0.00003
New Hampshire	0.0228	0.0019	0.00003	0	0.0368	0.0005	0.0394	0.00003
New York	0.0528	0.0019	0.0359	0	0.0376	0.0005	0.0329	0.00003
North Dakota	0.0190	0.0019	0.00003	0	0.0288	0.0005	0.0108	0.00003
Oklahoma	0.0427	0.0019	0.0033	0	0.0367	0.0005	0.0105	0.00003
Oregon	0.0055	0.0019	0.00003	0	0.0260	0.0005	0.0350	0.00003
Pennsylvania	0.0893	0.0019	0.2643	0	0.0572	0.3505	0.0545	0.00003
Rhode Island	0.0003	0.0019	0.00003	0	0.0219	0.0005	0.0303	0.00003
South Carolina	0.0450	0.0019	0.0936	0	0.0258	0.0005	0.0047	0.00003
South Dakota	0.0003	0.0019	0.00003	0	0.0290	0.0005	0.0257	0.00003
Texas	0.1500	0.1786	0.1156	1	0.0307	0.0529	0.0635	0.0001
Utah	0.0003	0.0019	0.00003	0	0.0217	0.0005	0.0260	0.00003
Vermont	0.0025	0.0019	0.00003	0	0.0272	0.0005	0.0269	0.00003
Washington	0.0098	0.0019	0.00003	0	0.0086	0.2443	0.0446	0.2277
West Virginia	0.0644	0.0019	0.0866	0	0.0234	0.0005	0.0210	0.00003
Wyoming	0.0056	0.0019	0.00003	0	0.0275	0.0005	0.0221	0.00003

Table B2: Unit weights for synthetic difference-in-differences and synthetic control (fuel-specific).

	Commercial		Electric		Industrial		Residential		Transportation	
	SDID	SC	SDID	SC	SDID	SC	SDID	SC	SDID	SC
Alaska	0.0049	0.00003	0.0463	0.0044	0.0225	0.0002	0.0099	0.00004	0.0616	0.00002
Arizona	0.0208	0.00003	0.0081	0.0088	0.0034	0.0002	0.0186	0.1221	0.00008	0.1254
Arkansas	0.0376	0.00003	0.0002	0.0044	0.0101	0.0002	0.0304	0.00004	0.0223	0.00002
California	0.0277	0.00003	0.1134	0.2107	0.1355	0.0002	0.0663	0.00008	0.0056	0.00008
Colorado	0.0483	0.00003	0.0002	0.0044	0.1139	0.0072	0.0048	0.00004	0.00008	0.00002
Connecticut	0.0198	0.00003	0.0002	0.0044	0.0034	0.0002	0.0224	0.00004	0.0053	0.0589
Delaware	0.0196	0.00003	0.0002	0.0044	0.0073	0.0002	0.0250	0.00004	0.0036	0.00002
District of Columbia	0.0128	0.00003	0.0002	0.0044	0.0002	0.0002	0.0189	0.00004	0.0044	0.00002
Georgia	0.0217	0.0005	0.0546	0.0752	0.0671	0.1822	0.0158	0.00004	0.00008	0.00002
Hawaii	0.0155	0.0673	0.0002	0.0044	0.0002	0.0002	0.0102	0.00004	0.0362	0.00002
Idaho	0.0135	0.0800	0.0002	0.0044	0.0219	0.3798	0.0076	0.5634	0.0315	0.0313
Illinois	0.1239	0.0003	0.0791	0.0044	0.0002	0.0002	0.1130	0.00004	0.00008	0.00002
Kansas	0.0237	0.00003	0.0444	0.0044	0.0655	0.0209	0.0358	0.00004	0.0731	0.4860
Maine	0.0475	0.00003	0.0181	0.0044	0.0057	0.0002	0.0340	0.0627	0.0303	0.00002
Maryland	0.0364	0.00003	0.0288	0.0044	0.0487	0.0002	0.0390	0.00004	0.00008	0.00002
Massachusetts	0.0514	0.00003	0.0002	0.0044	0.0519	0.0002	0.0489	0.00004	0.0372	0.0009
Mississippi	0.0212	0.00003	0.0308	0.0044	0.0687	0.2973	0.0205	0.00004	0.0638	0.00002
Missouri	0.0162	0.00003	0.0407	0.0044	0.0621	0.0002	0.0335	0.00004	0.0655	0.00002
Montana	0.0323	0.0972	0.0190	0.0044	0.0002	0.0002	0.0090	0.00004	0.0219	0.00002
Nebraska	0.0377	0.00003	0.0022	0.0044	0.0174	0.0002	0.0204	0.00004	0.0237	0.00002
Nevada	0.0161	0.00003	0.0002	0.0044	0.0002	0.0006	0.0167	0.00004	0.00008	0.0014
New Hampshire	0.0284	0.00003	0.0144	0.0044	0.0366	0.1708	0.0287	0.00004	0.0124	0.00002
New York	0.0686	0.00003	0.0095	0.0044	0.0002	0.0016	0.0551	0.0004	0.00008	0.00002
North Dakota	0.0238	0.00003	0.0155	0.0044	0.0217	0.0002	0.0129	0.00004	0.0625	0.00002
Oklahoma	0.0188	0.00003	0.0231	0.0044	0.0145	0.0002	0.0276	0.00004	0.0326	0.00002
Oregon	0.0072	0.00003	0.0252	0.0044	0.0002	0.0002	0.0205	0.00004	0.0171	0.00002
Pennsylvania	0.0069	0.4905	0.0608	0.1151	0.0445	0.0002	0.0937	0.1209	0.1126	0.00002
Rhode Island	0.0159	0.00003	0.0002	0.0044	0.0002	0.0002	0.0288	0.00004	0.00008	0.00002
South Carolina	0.0049	0.2619	0.0525	0.0044	0.0507	0.0002	0.0233	0.0016	0.00008	0.00002
South Dakota	0.0232	0.00003	0.0002	0.0044	0.0037	0.0002	0.0204	0.00004	0.0425	0.00002
Texas	0.0730	0.00003	0.1007	0.4465	0.0712	0.1108	0.0220	0.00004	0.00008	0.00002
Utah	0.0189	0.00003	0.0002	0.0044	0.0002	0.0002	0.0048	0.00004	0.0212	0.0835
Vermont	0.0135	0.00003	0.0075	0.0044	0.0247	0.0051	0.0180	0.00004	0.0131	0.00002
Washington	0.0234	0.00040	0.0412	0.0044	0.0002	0.0002	0.0048	0.0002	0.0563	0.2118
West Virginia	0.0070	0.0010	0.1293	0.0127	0.0256	0.0002	0.0245	0.1275	0.0775	0.00002
Wyoming	0.0178	0.00003	0.0324	0.0044	0.0002	0.0002	0.0141	0.00004	0.0655	0.00006

Table B3: Unit weights for synthetic difference-in-differences and synthetic control (sectoral-specific).

	Total			Coal		
cohort ($a \in \mathcal{A}$)	w/o Cov.	w/ Cov.	Projected	w/o Cov.	w/ Cov.	Projected
2000 (1)	9.7192	9.6583	9.1438	-9.5277	-10.709	-10.090
	(1.1184)	(1.2049)	(1.0903)	(3.7849)	(3.7714)	(3.6460)
2003 (2)	-1.8860	-0.9686	-1.2205	-7.9817	-7.5445	-7.5900
	(2.0055)	(1.9433)	(1.8442)	(3.7971)	(4.3269)	(4.2238)
2007 (1)	-10.396	-10.438	-9.1503	0.0539	0.8998	0.6419
	(1.9365)	(2.0321)	(2.3888)	(1.0538)	(1.7950)	(2.6256)
2011 (1)	-23.638	-31.282	-22.113	-10.913	-16.202	-12.687
	(7.4453)	(7.9711)	(6.6397)	(5.6195)	(8.8945)	(5.6028)
2012 (3)	-13.874	-13.873	-13.3294	-8.0848	-8.0696	-7.7753
	(5.6997)	(5.7838)	(5.3068)	(8.1649)	(8.1162)	(8.4988)
2013 (1)	-8.0181	-8.6989	-7.3739	3.4919	3.3737	3.5555
	(2.2557)	(2.5293)	(2.1471)	(7.8821)	(7.7925)	(8.3158)
2015 (4)	-0.2228	-0.3715	-0.1923	-3.1278	-3.2404	-3.3692
	(2.1178)	(2.0924)	(1.9290)	(3.5924)	(4.0067)	(3.7399)
2016 (1)	-5.0769	-5.1922	-5.6557	-10.251	-10.161	-10.057
	(1.6420)	(1.6110)	(1.6186)	(1.3882)	(1.3667)	(1.5421)
2017 (1)	-8.2666	-8.3890	-7.7141	-6.1182	-6.0480	-6.3009
	(2.0497)	(2.1872)	(2.1693)	(1.2906)	(1.3728)	(1.3409)

	Natural gas			Petroleum		
cohort ($a \in \mathcal{A}$)	w/o Cov.	w/ Cov.	Projected	w/o Cov.	w/ Cov.	Projected
2000 (1)	26.565	27.085	26.603	-4.0844	-4.1876	-4.7254
	(1.4293)	(1.4283)	(1.2850)	(1.1553)	(1.3192)	(1.4139)
2003 (2)	4.0621	3.7727	4.0022	0.6903	0.6402	0.8836
	(2.8291)	(2.7064)	(2.7643)	(2.2346)	(2.2577)	(1.7825)
2007 (1)	1.5374	1.4889	1.7141	-12.127	-12.037	-10.264
	(1.9580)	(2.2420)	(2.5259)	(1.5951)	(1.4343)	(1.4885)
2011 (1)	6.0221	6.2257	6.7757	-2.4987	-2.4460	-1.5282
	(1.3282)	(1.9069)	(1.5119)	(2.7938)	(2.3956)	(2.5723)
2012 (3)	3.8009	3.8111	3.8642	-7.8388	-7.5766	-5.6933
	(3.3327)	(3.4746)	(3.5612)	(6.2073)	(5.5483)	(4.7563)
2013 (1)	-7.7166	-7.9183	-7.4463	0.2108	0.3152	1.2056
	(5.9116)	(5.9489)	(6.3837)	(0.8451)	(0.7819)	(0.5292)
2015 (4)	0.2814	0.3311	0.3676	0.6361	0.7464	0.8396
	(1.8949)	(1.9936)	(2.0110)	(0.9791)	(0.9874)	(0.9564)
2016 (1)	2.8304	2.6874	2.8556	-1.1957	-1.2353	-1.3731
	(1.7222)	(1.1724)	(1.5741)	(1.9266)	(2.2906)	(2.2170)
2017 (1)	2.0229	2.0896	2.1263	-0.7637	-1.1402	-0.2457
	(0.3766)	(0.5109)	(0.6346)	(0.5258)	(0.6034)	(0.6472)

Table B4: Cohort-specific average treatment effects on the treated (τ_a) under staggered adoption (fuel-specific). Each cohort corresponds to a treated state and its first year of coal-fired unit retirement or refueling associated with a Clean Air Act enforcement settlement (see Table B1). The year listed in each row denotes the treatment onset year for that state, and the index in parentheses distinguishes multiple states sharing the same treatment year. ATT values are expressed in million metric tons (MMT), and standard errors are reported in parentheses.

	Commercial			Electric			Industrial		
cohort ($a \in \mathcal{A}$)	w/o Cov.	w/ Cov.	Projected	w/o Cov.	w/ Cov.	Projected	w/o Cov.	w/ Cov.	Projected
2000 (1)	2.0517	2.0548	1.9517	-1.3187	-1.3610	-1.3672	-2.2370	-2.6030	-2.7001
	(0.1549)	(0.1418)	(0.1455)	(1.7073)	(1.7470)	(1.5688)	(0.4916)	(0.5592)	(0.5303)
2003 (2)	0.2754	0.2520	0.3155	-3.1617	-2.4765	-3.0149	-2.5438	-2.0486	-2.3495
	(0.1624)	(0.1737)	(0.2515)	(2.2253)	(2.2697)	(2.2730)	(0.5187)	(0.5791)	(0.4001)
2007 (1)	0.7898	1.0115	1.0090	2.6291	2.8194	2.5461	-1.5214	-3.1105	-0.7581
	(0.2020)	(0.3137)	(0.2630)	(1.0169)	(1.0440)	(1.5419)	(0.7204)	(1.0509)	(0.6762)
2011 (1)	-0.2950	-0.2062	-0.1497	-13.436	-19.695	-13.858	-7.9442	-9.7470	-7.4776
	(0.2441)	(0.2589)	(0.2908)	(2.1292)	(2.6347)	(2.0740)	(1.6423)	(2.1012)	(1.3712)
2012 (3)	0.2079	0.2301	0.2311	-8.3925	-8.3827	-8.3709	-0.5089	-0.4447	0.1174
	(0.2638)	(0.2667)	(0.2945)	(5.6993)	(5.9588)	(5.9354)	(1.5009)	(1.5485)	(1.9047)
2013 (1)	-0.1468	-0.1548	-0.0686	-1.6993	-1.8972	-1.7633	-2.5633	-2.5110	-2.1065
	(0.0850)	(0.0945)	(0.0979)	(2.4159)	(2.3838)	(2.5179)	(1.1206)	(1.1751)	(0.9922)
2015 (4)	-0.1659	-0.1856	-0.1622	-1.0688	-2.0170	-1.1961	0.5744	0.5642	0.6848
	(0.2881)	(0.3064)	(0.2911)	(1.9483)	(2.0609)	(2.0191)	(1.0309)	(1.0623)	(1.1308)
2016 (1)	0.0474	0.0445	-0.0353	-4.7242	-4.6146	-4.6749	-4.1813	-3.8039	-3.1887
	(0.2034)	(0.2202)	(0.2745)	(0.3951)	(0.5284)	(0.4820)	(2.2246)	(2.1068)	(1.5867)
2017 (1)	-0.0714	-0.0614	0.0009	-7.3427	-7.3416	-7.4121	-0.9017	-0.9476	-0.5833
	(0.0713)	(0.0671)	(0.0617)	(1.2294)	(1.2948)	(1.2258)	(0.6606)	(0.9193)	(0.6864)

	Residential			Transportation		
cohort ($a \in \mathcal{A}$)	w/o Cov.	w/ Cov.	Projected	w/o Cov.	w/ Cov.	Projected
2000 (1)	0.0599	0.0211	0.0179	12.727	13.261	12.537
	(0.2872)	(0.1667)	(0.3064)	(0.5307)	(0.6202)	(0.5087)
2003 (2)	-0.1236	-0.1269	-0.0831	1.2483	1.1388	1.52115
	(0.2105)	(0.2403)	(0.2991)	(1.9962)	(1.9705)	(1.8246)
2007 (1)	0.6238	0.7207	0.7912	-8.3867	-8.0998	-7.1540
	(0.2225)	(0.2479)	(0.2456)	(2.0547)	(1.9814)	(1.6876)
2011 (1)	0.0234	0.1308	0.0436	0.2396	-2.2039	0.3006
	(0.1727)	(0.1679)	(0.1606)	(1.4435)	(1.4428)	(1.4913)
2012 (3)	0.0092	0.01435	0.1100	-0.5873	-0.6655	-0.9279
	(0.1573)	(0.1849)	(0.2568)	(3.0592)	(3.0840)	(2.8982)
2013 (1)	-0.3251	-0.2447	-0.2090	1.1271	1.1188	1.1250
	(0.0819)	(0.1226)	(0.1029)	(0.7335)	(0.7305)	(0.5542)
2015 (4)	0.2267	0.2149	0.2516	0.3913	0.4026	0.4394
	(0.1689)	(0.1641)	(0.1472)	(0.0811)	(0.8283)	(0.8135)
2016 (1)	0.5719	0.4964	0.6462	-1.4477	-1.7756	-1.5397
	(0.3158)	(0.3095)	(0.2995)	(0.8478)	(0.9565)	(0.8169)
2017 (1)	-0.2356	-0.2291	-0.1988	1.9541	1.9766	2.1353
	(0.0642)	(0.0673)	(0.0492)	(0.2536)	(0.2389)	(0.3057)

Table B5: Cohort-specific average treatment effects on the treated (τ_a) under staggered adoption (sectoral-specific). Each cohort corresponds to a treated state and its first year of coal-fired unit retirement or refueling associated with a Clean Air Act enforcement settlement (see Table B1). The year listed in each row denotes the treatment onset year for that state, and the index in parentheses distinguishes multiple states sharing the same treatment year. ATT values are expressed in million metric tons (MMT), and standard errors are reported in parentheses.

	without Covariate	with Covariate	Projection Method
Natural gas energy-related carbon dioxide emission			
ATT	5.361	5.368	5.465
Standard error	(3.616)	(3.672)	(3.709)
Petroleum energy-related carbon dioxide emission			
ATT	-3.014	-2.967	-2.234
Standard error	(2.235)	(2.028)	(1.725)
Commercial energy-related carbon dioxide emission			
ATT	0.376	0.397	0.410
Standard error	(0.276)	(0.280)	(0.269)
Residential energy-related carbon dioxide emission			
ATT	0.076	0.087	0.130
Standard error	(0.137)	(0.140)	(0.150)
Transportation energy-related carbon dioxide emission			
ATT	1.214	1.095	1.313
Standard error	(2.488)	(2.525)	(2.300)
Time FE	✓	✓	✓
State FE	✓	✓	✓

Table B6: Synthetic difference in differences estimates with staggered adoption (others). Standard errors are clustered at the unit level and computed using bootstrap methods. The third column applies the Kranz-style projection method, which adjusts for covariates by projecting them out based on untreated observations (Kranz, 2022; Clarke et al., 2024). Standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.