Enforcing Clean Air, Achieving Climate Benefits

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Abstract

This study evaluates the climate effects 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) estimator to U.S. state-level panel data from 1998 to 2022 to estimate the causal impact of this intervention on CO_2 emissions. 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).

Numerous studies have 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). These findings suggest that enforcement-based policies may complement carbon pricing in accelerating decarbonization.

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) sued Duke (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 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 deep decarbonization unless it compels technological or fuel substitution (Aldy and Pizer, 2015; Fowlie and Muller, 2019).
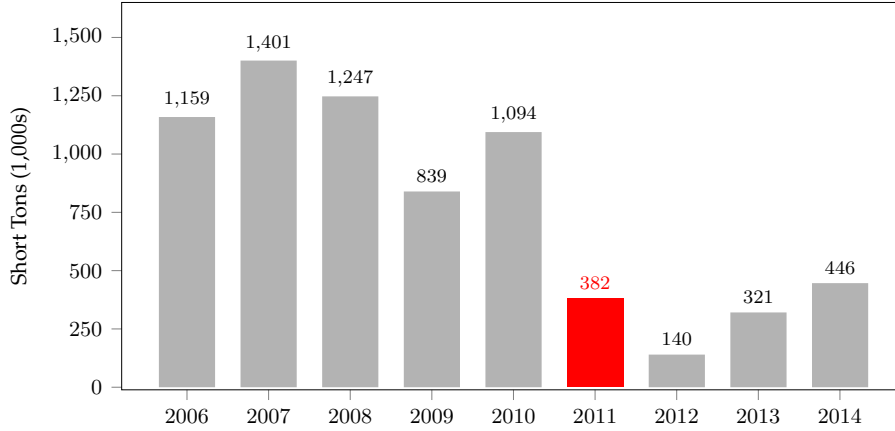
Figure 1: Coal Consumption at Gallagher Power Plant. The sharp decline in 2011 reflects the implementation phase of the 2009 consent decree.

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 SO_2 emissions. This first phase of reductions lasted until January 30, 2011, after which time allowable emission levels became more stringent. Finally, Duke Energy needed to choose whether to refuel or shutdown generators 1 and 3 by January 1, 2012. The final shutdown needed to be completed by February 1, 2012. In Figure 1, there's a rather dramatic reduction in coal consumption starting in 2011, that coincides with the second phase of emission targets. Ultimately, Duke Energy elected to shutdown these generators.

Our analysis uses state-level panel data from 1998 to 2022 to construct a counterfactual emission 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 (Abadie et al., 2010; Arkhangelsky et al., 2021).

Our results indicate that the 2009 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 emission cuts 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 emission 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 billions of dollars in environmental benefits, reinforcing the economic case for strict 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 climate 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

Coal-fired power plants are major contributors to both local air pollution and global greenhouse gas emissions (Graff Zivin and Neidell, 2013). In the United States, coal combustion alone accounts
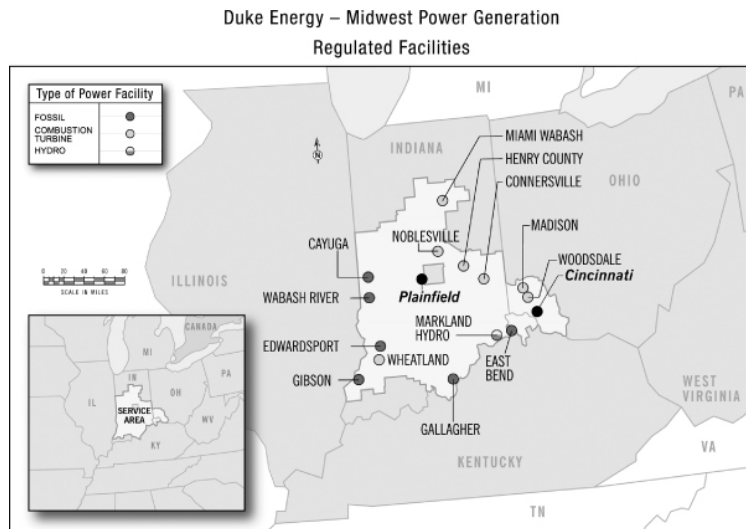
Figure 2: Geographic Distribution of Duke Energy's Regulated Power Generation Facilities in Indiana. Source: Form 10-K (2008), U.S. Securities and Exchange Comission. U.S. SEC. (2009)

for a significant share of energy-related CO_2 emissions, along with harmful co-pollutants such as SO_2, NO_x, and mercury. Given the environmental and public health risks associated with these emissions, the EPA has increasingly relied on the Clean Air Act's NSR provisions to bring older coal-fired units into compliance through retrofits or fuel switching (EPA 2009b).

One of the most consequential enforcement cases under this initiative involved Duke Energy's Gallagher Generating Station in New Albany, Indiana. Built in the 1950s and comprising four coal-fired units, the Gallagher Plant had long been a significant emitter of CO_2 and SO_2. In 1999, the EPA and the DOJ filed a lawsuit alleging that Duke Energy (then Cinergy) had made major modifications to Units 1 and 3 without installing best-available pollution controls or acquiring the necessary permits, in violation of the NSR provisions of the Clean Air Act and the Indiana State Implementation Plan (EPA 2009a). After a decade of litigation, a federal jury in Indianapolis found in May 2009 that Duke had indeed violated the law by modifying the units in ways that led to substantial increases in SO_2 emissions without the required pollution control technology (EPA 2009a). Figure 2 shows the location of the Gallagher Plant in southern Indiana.

In response to these findings, a partial consent decree was entered in late 2009. Under the terms of the settlement, Duke agreed to either repower Units 1 and 3 with natural gas or permanently shut them down. The company also committed to installing Dry Sorbent Injection (DSI) technology on Units 2 and 4. These actions were expected to reduce SO_2 emissions at the Gallagher Plant by approximately 35,000 tons per year, an 86% reduction compared to 2008 levels (EPA 2009b). The conversion of Units 1 and 3 to natural gas was projected not only to eliminate SO_2, mercury, and

4

particulate matter emissions from those units, but also to reduce their carbon dioxide emissions by roughly 50% per unit of electricity generated (EPA 2009b).

The consent decree also required Duke to pay a $1.75 million civil penalty and invest $6.25 million in environmental mitigation projects, including land conservation, hybrid vehicle conversions, and renewable energy upgrades (EPA 2009b). These measures reflect the federal government's strategy of combining enforcement with broader environmental co-benefits. As noted by EPA officials at the time, the case was emblematic of how targeted enforcement against local pollution sources could yield ancillary reductions in global climate pollutants (EPA 2009b).

While the Duke Gallagher case was part of a broader EPA initiative targeting non-compliant coal-fired power plants, it stands out in several important respects. Most NSR settlements reached during the 2000s required end-of-pipe controls (e.g., scrubbers) to reduce SO_2 and NO_x emissions, but rarely involved fuel switching (EPA 2023). In contrast, the Gallagher decree explicitly mandated either permanent shutdown or full conversion to natural gas—resulting in a structural change in fuel use and a direct reduction in CO_2 emissions (EPA 2009b; EPA 2009a).

Other states did face enforcement actions during the 2000s. However, these cases typically did not entail comparable mandates to eliminate coal combustion or substitute natural gas on this scale (EPA 2023). Moreover, none of the states in our control group were subject to a similar magnitude of CO_2-relevant structural change in 2009, making Indiana a unique treatment case. This contextual difference strengthens the validity of our identification strategy.

The Gallagher case thus provides a natural policy shock—one that is exogenous to CO_2-specific regulation but nonetheless induced a significant fuel transition at a major emitter. This setting offers a valuable opportunity to examine the extent to which non-climate air quality enforcement can influence carbon emissions at the state level. In this paper, we exploit the 2009 Duke Energy settlement as a quasi-experimental policy intervention and estimate its causal impact on energy-related carbon dioxide emissions in Indiana. Using a SDID approach, we examine both aggregate and sector-specific emission trajectories before and after the intervention, focusing on whether the shift away from coal led to persistent reductions in CO_2 emissions from electric power generation and related sectors.

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 reweighting of units and time periods. This enhances robustness to unobserved confounding and non-parallel trends [1].

Let Y_{it} denote the observed emissions for state $i \in \{1, ..., N\}$ at time $t \in \{1, ..., T\}$. 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 SDID estimator computes the average treatment effect on the treated (ATT), denoted τ, by solving the following weighted least squares problem:

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

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.

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 $\lambda_t \geq 0$ [2].

These weights enable a weighted DID estimator for ATT:

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

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

[2] 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).

where

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

To improve precision and reduce confounding, we include time-varying covariates X_{it} by applying a residualization step. We regress Y_{it} on covariates X_{it} to derive γ, and then compute residualized outcomes:

$$\hat{Y}_{it} = Y_{it} - X_{it}'\hat{\gamma}. \quad (6)$$

The SDID estimator is then applied to $\hat{Y}_{it}$ (Arkhangelsky et al., 2021; Clarke et al., 2024).

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

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

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). Furthermore, the placebo inference offers an intuitive falsification test: if the policy truly had no effect, we would expect Indiana's estimated ATT to fall within the distribution of placebo effects. Instead, we find Indiana's ATT is among the most extreme, reinforcing the credibility of a genuine treatment effect.

4 Data

To estimate the impact of state-level carbon emissions policy, we assemble a 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, aligning with the regulatory targets of most state-level carbon mitigation policies.

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

	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.

plausibility of the identification strategy and reducing omitted variable bias in the treatment effect estimation.

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. 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 [3].

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. 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, such as the mandated shutdown of Units 1 and 3 and the repowering of Units 2 and 4 with natural gas by mid-2012. 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.

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

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[3]List of excluded states and details are denoted in Table A1

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. 86.14 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 more 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 in 2009.

5 Results

5.1 Synthetic difference in difference estimation

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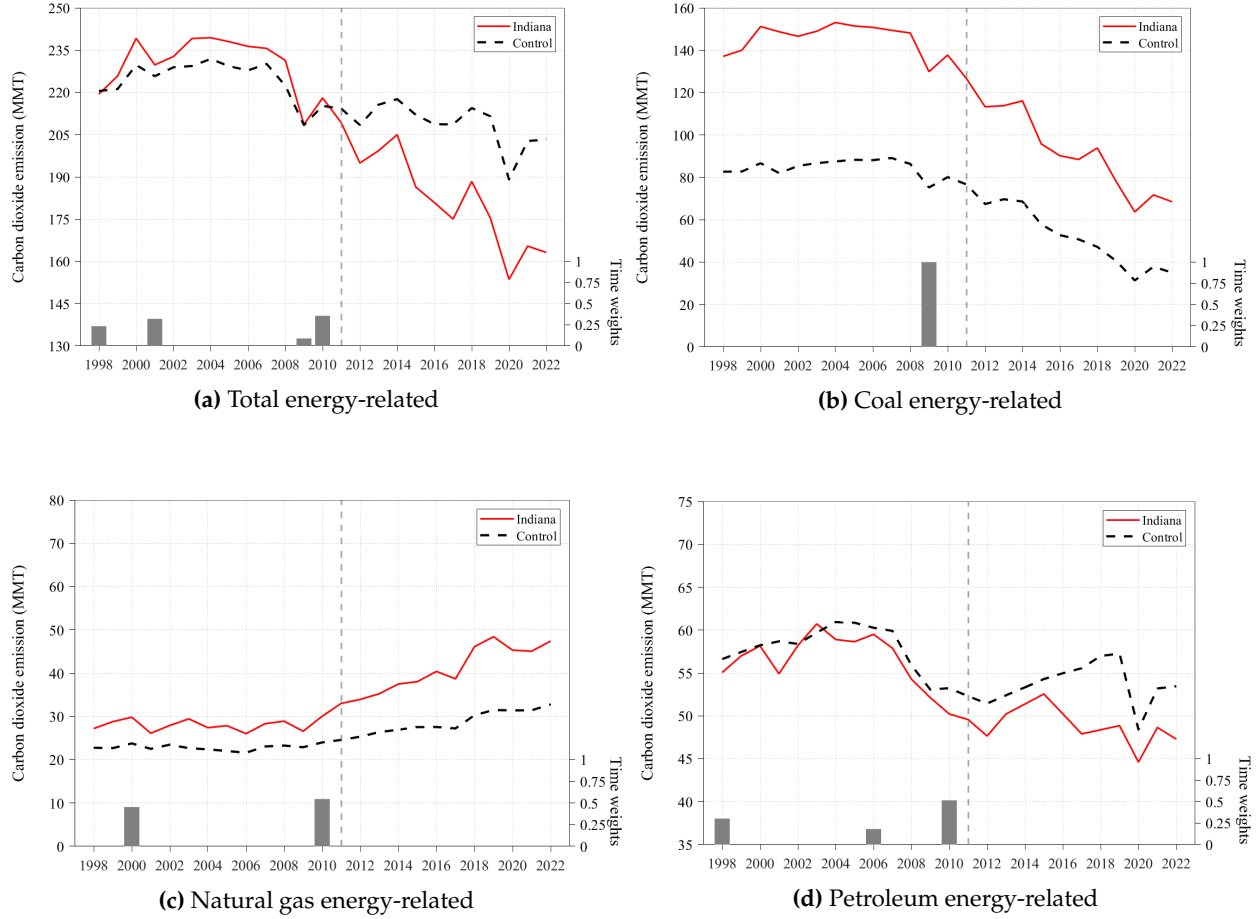
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Figure 3: Outcome Trends and Time-Specific Weights (fuel specific emission). (a)–(d) show treatment and control comparisons across different outcomes.

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 3, 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.,

11

	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.

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 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 3 (b), reinforcing the causal interpretation that the Gallagher plant settlement produced a targeted and sustained reduction in coal combustion emissions.

(a) Commercial energy-related

(b) Electric power energy-related

(c) Industrial energy-related

(d) Residential energy-related

(e) Transportation energy-related
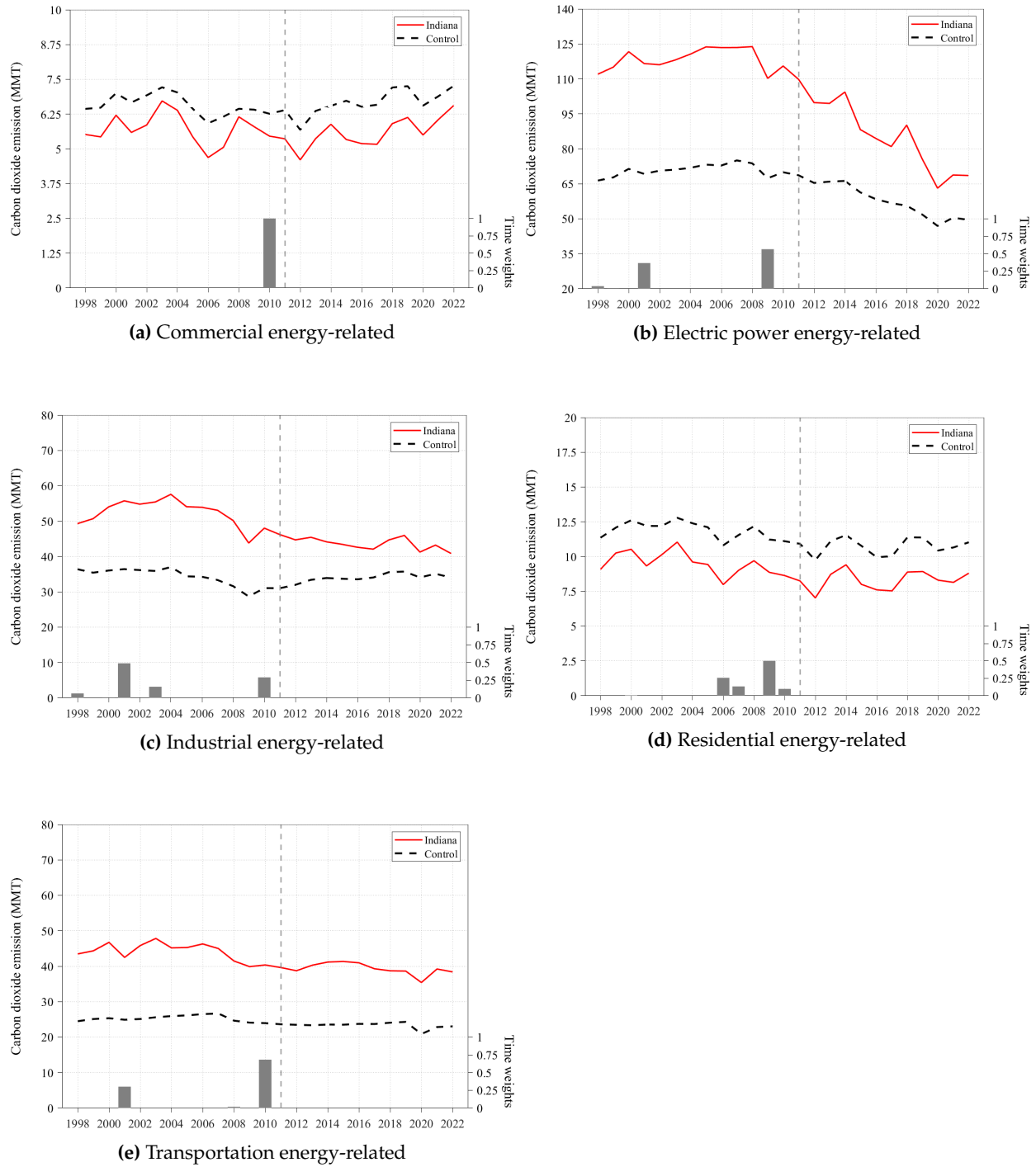
Figure 4: Outcome Trends and Time-Specific Weights (sectoral specific emission). (a)–(e) show treatment and control comparisons across different outcomes.

Figure 4 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 3, the most notable divergence occurs in the

	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 $\hat{V}_{placebo}(\hat{\tau}) = \mathrm{Var}(\hat{\tau}_p)$, 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.

electric power sector (Panel b), where Indiana's emissions declined substantially relative to the 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 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 presented in Figure 4, 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 A2 and A3. 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 A2), 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 A3), 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: its ability to flexibly reweight both units and time periods while incorporating covariate adjustment to improve 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 5 displays the estimated event-time effects across four energy-related outcomes. Panels (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.

Figure 6 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

(a) Total energy-related

(b) Coal energy-related

(c) Natural gas energy-related

(d) Petroleum energy-related
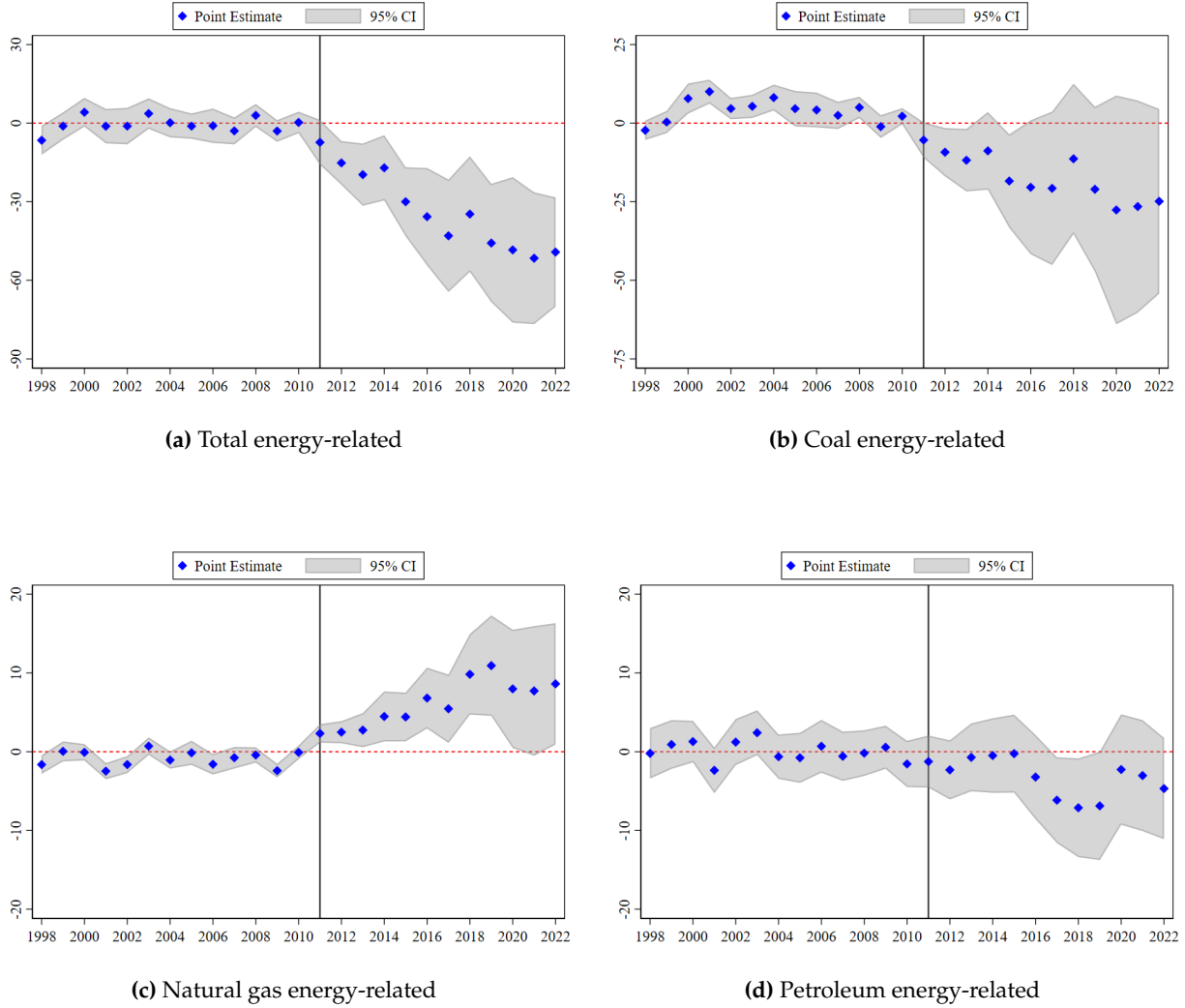
Figure 5: **Event Studies (fuel specific emission)**. (a)–(d) show event studies acorss different outcomes.

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.
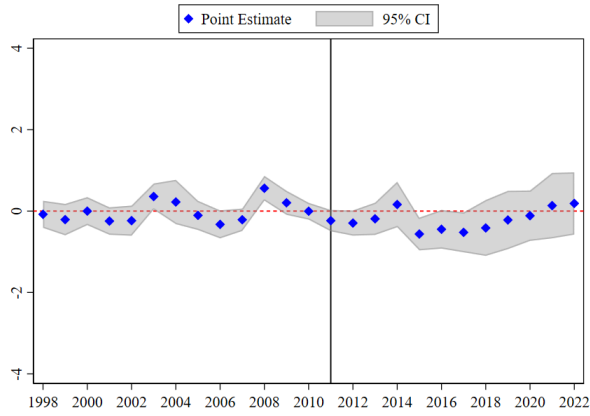
(a) Commercial energy-related
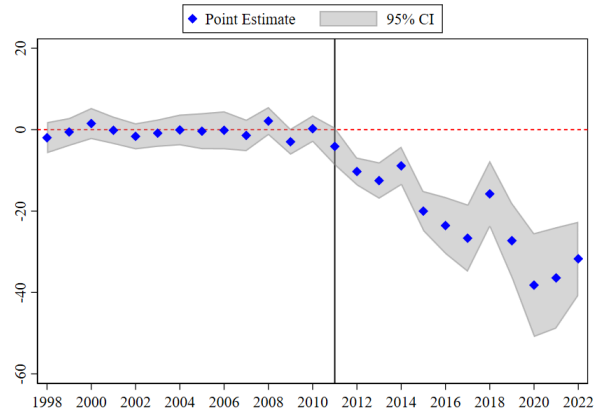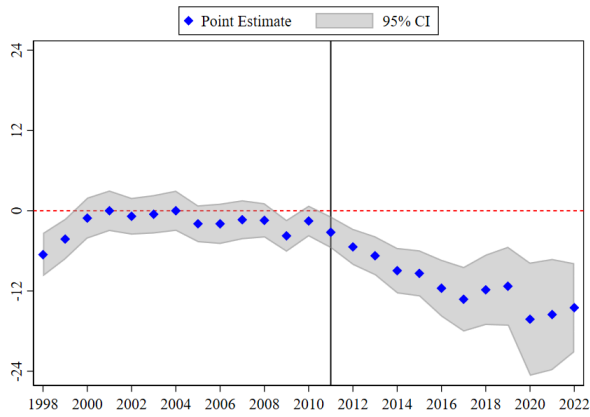
(b) Electric power energy-related

(c) Industrial energy-related
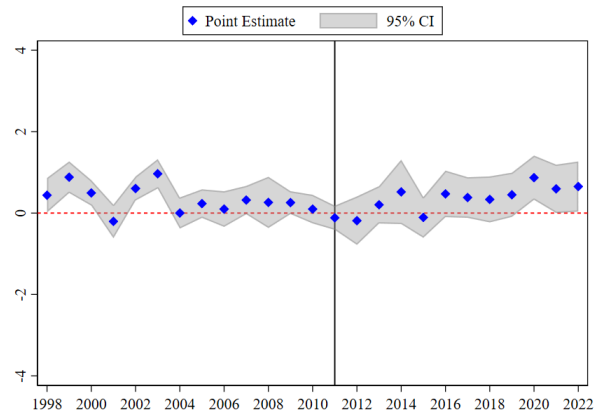
(d) Residential energy-related
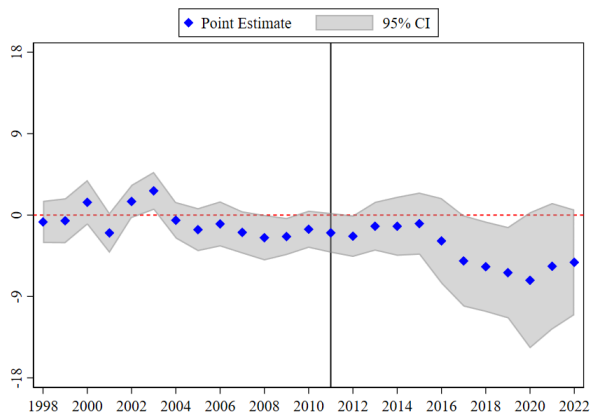
(e) Transportation energy-related

Figure 6: Event Studies (sectoral specific emission). (a)–(e) show event studies acorss different outcomes.

5.3 Staggered Adoption Analysis

While the Indiana Gallagher plant case offers a clear and discrete intervention point, other states have also undertaken partial coal plant shutdowns or conversions over the past two decades. To extend the policy relevance of our findings, we estimate a staggered adoption specification in which the treatment group includes not only Indiana, but also 14 additional states that implemented major coal-fired unit retirements at varying points in time. Each treated unit is assigned its own adoption year, defined as the first year a key coal unit was permanently decommissioned or repowered to natural gas.

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

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

where T_{post}^a 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 [4] . The projection method proposed by 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

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[4] $\hat{\tau}_a$ for each cohorts ($a \in \mathcal{A}$) are denoted in Tables A4 and A5.

	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 A6.

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 driven by federal enforcement or broader economic and regulatory pressures—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. Treating SCC as constant over the observed range of emission reductions enables a tractable yet policy-relevant

	Indiana (SDID)	U.S. (Staggered-SDID)
Total energy-related carbon dioxide emission		
	$ 15.77	
Coal energy-related carbon dioxide emission		
	$ 8.16	$ 3.94
Electric power energy-related carbon dioxide emission		
	$ 9.88	$ 2.11
Industrial energy-related carbon dioxide emission		
	$ 4.93	$ 1.33
		(Unit: billion)

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). All monetary values are in 2020 billion USD.

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. 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 post-period:

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

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 [5].

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 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

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

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.

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Appendix

A   Additional Figures and Tables

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 A1: 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 A2: 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 A3: Unit weights for synthetic difference-in-differences and synthetic control (sectoral-specific).

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

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

Table A4: 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 A1). 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.

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

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

Table A5: 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 A1). 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	1.213	1.095	1.313
Standard error	(2.488)	(2.525)	(2.300)
Time FE	✓	✓	✓
State FE	✓	✓	✓

Table A6: 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.