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Policy Analysis

Green Bond Issuance and Carbon Emissions: Can Causal Machine Learning Inform Forward-Looking Policy Decisions?

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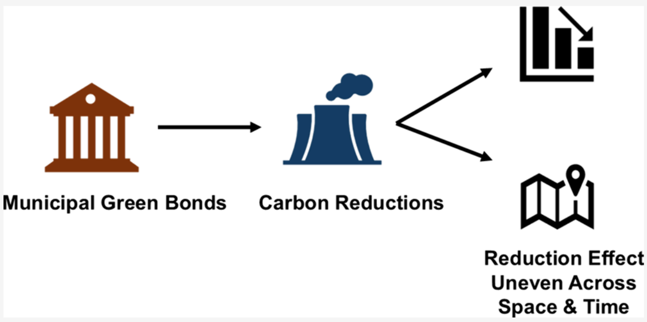
ABSTRACT: Green bonds finance projects intended to deliver environmental benefits, including reductions in greenhouse gas emissions. However, evidence that municipal green bond issuance lowers local carbon emissions remains limited and lacks the spatial and temporal granularity that municipalities need to make informed decisions. This study investigates the impact of U.S. municipal green bonds issued between 2009 and 2019 on carbon emissions while accounting for the confounding effects of local socioeconomic conditions. We employ a causal forest model within a double-biased machine learning framework to estimate the effects of issuance volume on emission trends. The analysis reveals substantial spatial and temporal heterogeneity: the largest reductions occur in specific counties and increase over time, with an implied abatement cost of \$192 per ton of CO_2. Counties with higher concentrations of small and medium enterprises exhibit the strongest benefits. Comparisons between counties with and without prior issuance suggest that new green bonds generally reduce emissions, although magnitudes vary with local economic and infrastructure characteristics. These findings provide evidence on the effectiveness of municipal green finance, with implications for policy implementation and forecasting environmental outcomes, particularly for first-time issuers.



KEYWORDS: *municipal green bonds, carbon emissions, casual machine learning, spatial heterogeneity, economic risks and uncertainties*

1. INTRODUCTION

The United States ranks among the world's highest in per capita energy consumption and is the second largest emitter of CO_2.[1,2] Paradoxically, the U.S. is also the largest issuer of green bonds, including municipal green bonds designed to finance projects in renewable energy, mass transit, and green buildings.[3] While these instruments hold potential for mitigating CO_2 emissions, empirical evidence is limited, particularly at granular local levels.

Existing studies on green bonds have primarily focused on the corporate sector, documenting favorable impacts on emissions.[4−7] Moreover, researchers have emphasized the importance of certification. Yeow and Ng[8] found that the environmental benefits of corporate green bonds materialize more consistently when bonds undergo third-party verification. Signaling theory[9,10] offers a conceptual underpinning for these findings, suggesting that the issuance of certified green bonds serves as a clear commitment to environmental sustainability. With the address of the information asymmetry between issuers and investors, who may otherwise lack sufficient information to discern the genuineness of the issuer's environmental goals, certification provides a credible signal of genuine environmental intent. Consequently, market reaction to these signals can translate into favorable pricing ("greenium") for certified bonds.[11−13] Despite these insights, the body of evidence on green municipal bonds remains comparatively sparse, particularly regarding their role in achieving actual, quantifiable carbon reductions.

Municipal green bonds differ from corporate green bonds in several ways. First, they finance infrastructure improvements with strong geographical and demographic linkages, such as roads, water systems, airports, and ports.[14] As a result, they can exert measurable localized influences on CO_2 emissions if they are used effectively. Second, their tax-exempt status often attracts different types of investors, potentially leading to distinct funding and monitoring mechanisms.[15] Third, this local dimension can magnify heterogeneity in outcomes, as socio-economic factors, such as per capita income, educational attainment, and commute times, vary considerably across municipalities.[16−18] These characteristics underscore the need for a more nuanced, spatially disaggregated examination of green municipal bonds to capture both the direct and indirect drivers of carbon reductions.

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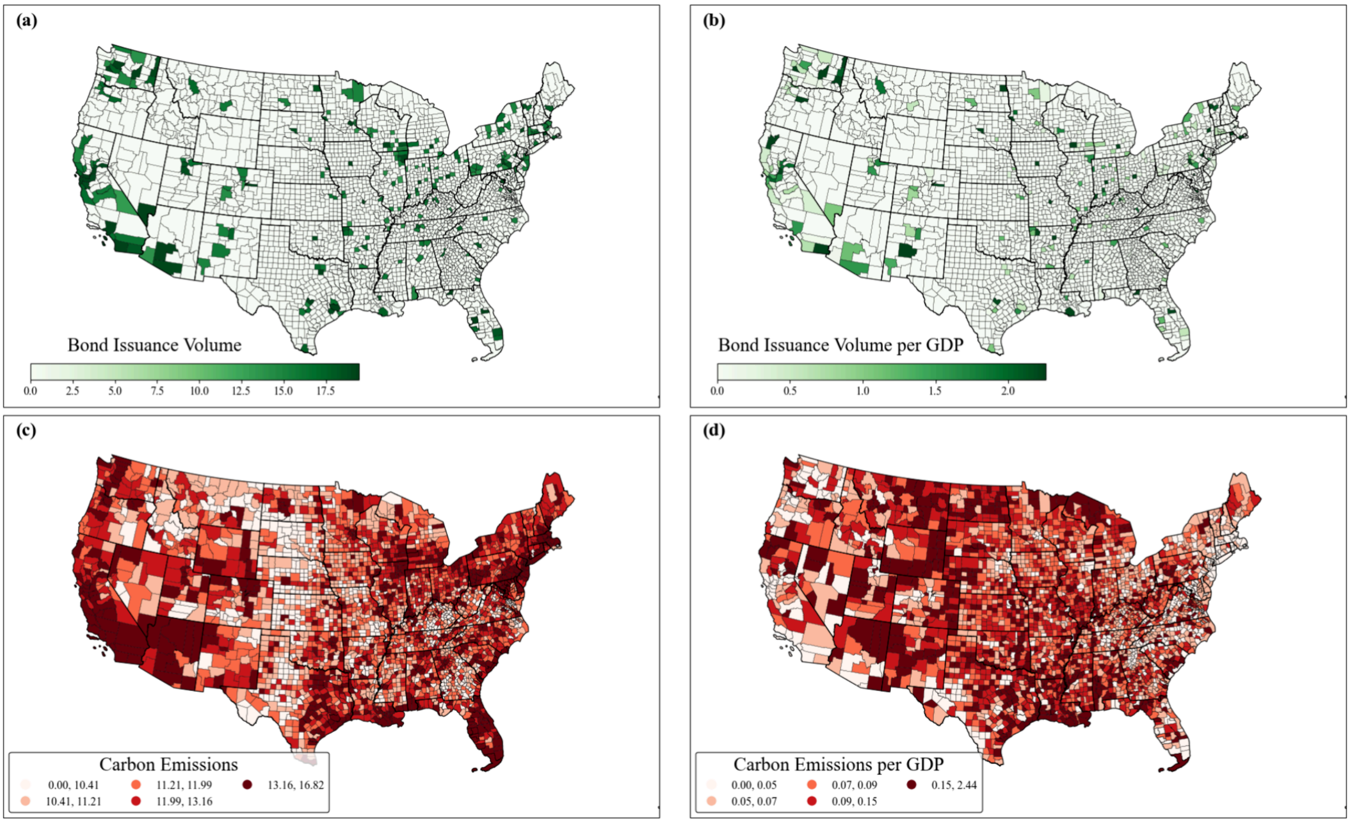

Figure 1. Geographical distribution of green bond issuance and carbon emissions across U.S. counties: (a) total green bond issuance volume, (b) green bond issuance intensity (volume normalized by GDP), (c) total carbon emissions, and (d) carbon emissions normalized by GDP.

However, the integrity of green municipal bonds is subject to greenwashing concerns, particularly if they are self-labeled without rigorous third-party oversight.[19−21] Although there are voluntary guidelines, such as the Green Bond Principles and certifications from the Climate Bonds Initiative, enforcement is not mandatory.[7] The absence of standardized monitoring and verification raises questions about whether the capital is indeed allocated to sustainable projects with tangible emission benefits or is merely conferring reputational advantages. Furthermore, the verification processes for green labels lack uniformity across different verifiers, which can result in significant discrepancies in environmental outcomes.

Furthermore, research on municipal green bonds must account for the delayed realization of environmental benefits from infrastructure development. Projects financed by green bonds often involve extensive planning and implementation, which postpones their potential impact on carbon emissions and, thus, on policy decisions to opt for these financial instruments.[22] Conventional linear regression models frequently fail to capture such delays and the nonlinear interdependencies that may emerge from interactions among economic resources, community demographics, and technological adoption rates.[12,13,23] Recent advancements in causal machine learning provide a framework to address such nonlinearities and uncover heterogeneous treatment effects at finer spatial scales.[24−26] Unlike conventional statistical methods or machine learning approaches, causal ML facilitates the estimation of individualized treatment effects, yielding interpretable and fine-grained heterogeneous results that traditional methods typically do not capture. For instance, the causal forest method,[24,25] a tree-based framework for causal inference, can produce uncertainty estimates beyond mere point predictions, thereby bolstering the robustness of analytical results. With the capture of both spatial and temporal heterogeneity, these approaches are particularly suited for analyzing how green bond issuance influences localized CO_2 emissions over multi-year horizons.

Building on these considerations, this study examines how municipal green bonds affect carbon emissions at the county level in the United States. It expands on existing literature by leveraging granular, region-specific data to investigate whether the time-lagged and heterogeneous benefits of green bonds are shaped by local socioeconomic conditions. Furthermore, the use of causal machine learning methods facilitates the exploration of nonlinear relationships, delivering a more nuanced understanding than conventional linear models can provide. Additionally, by incorporation of anticipated social development and urbanization patterns, this study adopts an *ex ante* perspective to explore how municipal green bond issuance may influence future carbon outcomes under evolving economic and demographic scenarios.

2. DATA AND METHODS

2.1. Data. In this study, we employ carbon emission data from the Vulcan version 3.0 data set, which provides annual carbon emission estimates at a 1 × 1 km resolution across the continental United States.[27] We aggregated these emission data to the county level for each year from 2010 to 2021. Preliminary examination indicates an overall decline in carbon emissions during this period. In the absence of uniform, publicly available data at the utility or bond level, county-level aggregation represents the most consistently feasible spatial

Table 1. Summary Statistics[a]

	mean	std dev	min	max
green bonds ($ million)	18.44	208.24	0.29	1304.24
emissions (ton of CO_2)	2457588.88	3636029.91	20024.12	21195479.51
housing estimates	94847.99	1587221.16	5134.00	10038388.00
poverty rate (%)	15.80	4.90	5.80	33.40
median household income ($)	51429.89	11019.37	28152.00	84627.00
gross domestic product ($ thousands)	60134982.98	102221907.02	174628.00	593671075.00
unemployment rate (%)	6.19	2.85	0.80	29.40
economic typology	1.81	2.02	0.00	5.00
education level (%)	36.76	11.51	6.61	62.86
net migration rate	1.40	12.82	(42.30)	89.30
commute time (min)	25.10	4.73	12.00	38.50
total employment (industry mix)	75438.51	121094.48	160.00	669990.00
payroll per employee ($ thousands)	67.99	24.20	36.10	183.39
avg establishment size	10.70	4.63	1.85	46.84
total electricity generation (GWh)	56914.08	133956.90	−2.03	1005809.00

[a]Housing estimates, which measure housing units at the county level, are derived from the Census American Community Survey (ACS). Poverty rate, median household income, commute time to work, education level, unemployment rate, and net migration rate data are sourced from the U.S. Department of Agriculture. Real gross domestic product (GDP), adjusted for inflation and expressed in thousands, along with economic typology classifications, is provided by the Bureau of Economic Analysis. The economic typology categories are as follows: 0, non-specialized; 1, farm-dependent; 2, mining-dependent; 3, manufacturing-dependent; 4, federal/state-government-dependent; and 5, recreation. The education level metric reflects the percentage of adults with a bachelor's degree or higher. The commute time estimate represents the average travel time from home to work. Total employment (count of employees in heavy-emission industries; NAICS: manufacturing, 31−33; construction, 23; utilities, 22; mining, 21; transportation and warehousing, 48−49; and agriculture, 11), payroll per employee (measures average annual compensation per worker, a proxy of local economic and technological intensity of production), and average establishment size (employees ÷ establishments; measures typical scale of business) are sourced from the County Business Patterns (CBP). Total electricity generation (county net generation aggregated from EIA Form 923 and EIA-860, in MWh) measures local electricity production and is from the U.S. Energy Information Administration (EIA). Due to the high skewness of the green bond size, emission data, and GDP, these variables have been log-transformed for the following analysis. All variables in this study are time series, except for the economic typology, which is based on 2015 data and serves as the primary economic typology type at the county level.

granularity for the present analysis. As illustrated in Figure 1c, the patterns of county-level carbon emissions are concentrated in highly populated and industrialized regions. In contrast, the emissions normalized by GDP (Figure 1d) highlight areas with economies that are particularly reliant on carbon-intensive industries. Figure S1 presents sectoral decomposition (residential, commercial, industrial, and electricity generation).

Data on municipal green bonds issued from 2009 to 2019 were acquired from Bloomberg Fixed Income Search, with bonds designated as "green" based on their green bond indicator. We limited our study period to this decade to encompass the entire history of green bonds and mitigate market volatility caused by the COVID-19 pandemic. One third of green bonds were issued by water authorities, followed by general obligation and financial authority bonds with sustainable purpose, with a smaller fraction of airport, transportation, and school/university bonds. While some evidence indicates that green bonds are less affected by disruptions during COVID, another study suggests that their efficiency diminished during the pandemic, albeit unevenly across different energy sources.[28,29] To ensure a temporally stable analysis, we excluded the pandemic years from our study. The curated data set comprises 8703 green bonds, which were aggregated at the county level to represent the total size of both traditional and green bond issuances. This aggregation resulted in 468 county−year observations spanning from 2009 to 2019, noting that a specific county may not issue bonds every year. Figure 1a maps the geographic distribution of U.S. green bond issuance and shows a pronounced concentration in major economic centers and urbanized regions. By contrast, Figure 1b reports bond intensity (issuance per unit of county GDP), which highlights jurisdictions where green bond activity represents a materially larger share of the local economic activity. Additionally, we compiled a data set to examine the impact of green bond issuance at the county level between 2009 and 2019, using a binary indicator for whether a green bond was issued. This data set comprises 37 716 county−year observations, of which 468 county−year observations recorded green bond issuances during the study period, while the remaining 37 248 did not have any such issuances.

In this analysis, county-level control variables include real gross domestic product (GDP), housing estimates, median household income, poverty rate, economic typology indicator, education level, net migration rate, average commute time, payroll per employee, average establishment size, and electricity generation. The rationale for selecting these variables is based on the widely recognized fact that economic conditions directly influence emission levels in a region.[30,31] Additionally, these variables may reflect the regional necessity to issue bonds, particularly those aimed at financing green projects.[32] The summary statistics in Table 1 present an overview of the statistical data for the variables analyzed in this study.

Note that the unconfoundedness assumption, an important concept in causal inference, posits that no unobserved confounders affect both the treatment and the outcome.[33] However, this assumption cannot be directly tested in observational studies. Although including confounders will help reduce bias in our analysis compared to previous studies, the potential for residual bias still exists due to the presence of unobserved confounders. To mitigate selection bias, we

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included all available samples of green municipal bonds and relevant economic indicators that could influence both the treatment and the outcome. However, caution is advised when interpreting the results, as these measures cannot fully eliminate the possibility of confounding biases.

In the correlation analysis of the selected control variables from Table 1, a significantly high correlation was observed between GDP, housing units, and employment (as shown in Figure S2). Additionally, median household income and poverty rates were identified as complementary economic measures. To address multicollinearity and enhance the robustness of the analysis, housing units, poverty rates, and total employment were excluded from the original set of variables.

2.2. Methods. Previous research in sustainable finance has extensively utilized linear models to explore the relationship between investment actions and their environmental outcomes. However, these models often confine the impact of financial instruments within a rigid dependency. Considering that this field is still in its nascent stages and rapidly evolving, it is highly unlikely that these relationships are perfectly linear or homogeneous.[34] To better understand the heterogeneity and confounders driving sustainability impacts in general and carbon emissions specifically, it is important to identify complex patterns embedded within this domain that potentially interact with other social or economic factors.

Machine learning facilitates the prediction of complex patterns underlying sustainable impacts. However, these tools are not inherently designed to estimate causal effects, which has spurred the development of causal machine learning. The primary goal of this type of model is to estimate causal effects within these complex patterns. Specifically, causal forests, an extension of random forests, preserve the core structure of random forests, such as random splitting and tree-based structure.[24] However, unlike traditional random forests that average over the trees for outcome prediction, causal forests are designed to estimate heterogeneous treatment effects, which maximize the treatment differences between trees. A potential limitation of this approach is that a small sample size or an excessively large number of covariates may pose significant challenges.

2.2.1. Conditional Average Treatment Effect (CATE). The average treatment effect (ATE) has traditionally served as the predominant metric for estimating causal inference. However, it often fails to capture the full spectrum of necessary information, particularly in instances where treatment effects exhibit systematic variation in relation to sample characteristics, referred to as the heterogeneity of treatment effects. CATE at covariate value x is the expected difference in potential outcomes under treatment and control conditional on $X = x$. Heterogeneous treatment effects can be estimated through CATE as below[35]

$$\theta(x) = E[Y|T = 1, X = x] - E[Y|T = 0, X = x] \tag{1}$$

where $Y(T)$ denotes the value of the outcome variables if we were to treat it with a treatment T, given a vector of features X. When computing average CATE across the set of variables, X, one can estimate CATE for a continuous treatment.

2.2.2. Causal Forest. Causal forest, a method derived from generalized random forests, was developed by Athey and Wagner specifically to estimate heterogeneous treatment effects.[24] This method has been tested across various domains, including healthcare, marine ecosystems, agricultural management, and fintech applications.[36,37] The primary objective of this method is to identify distinct subsets within the data where the treatment effect remains constant yet differs markedly from other subsets. Like conventional machine learning techniques, cross-validation is employed to prune the causal trees, enhancing the model's accuracy and preventing overfitting.

2.2.3. Double/Debiased Machine Learning (DML). DML relies on estimating so-called nuisance parameters by treating them as supervised learning problems and using them as plug-in estimates to solve for the causal parameter as presented in a partially linear model[38]

$$\log(Y_t) = \theta(X) \times \log(T_t) + g(X) + \varepsilon \tag{2}$$

$$\log(T_t) = f(X) + \eta \tag{3}$$

where T is the treatment variable, X is a vector of confounders/covariates, $g(X)$ represents the impact of X on Y, $f(X)$ represents confounder impact on T, g and f are nuisance parameters, and treatment and outcome are both a function of features X. It is important to note that emissions, green bond volume, and GDP within vector X have been log-transformed to account for right-skewed distributions. CATE $\theta(X)$ is estimated in a two-stage estimation procedure, where the first stage outcome and treatment are predicted from features X using ML models, individually. In the second stage, CATE $\theta(X)$ is estimated by solving

$$\hat{\theta} = \arg\min E[(\tilde{Y} - \theta(X)\cdot\tilde{T})^2] \tag{4}$$

where $\tilde{Y}$ values are the residuals of the estimation of Y as a function of X and $\tilde{T}$ values are the residuals of the estimation of T as a function of X.

3. RESULTS AND DISCUSSION

3.1. Causal ML Performance Assessment. The lagged effects of carbon emission reductions assume that the environmental benefits of investments funded through green bonds may not be immediately evident. Hence, we adjusted the CO_2 emission data by shifting it between 1 and 3 years to synchronize with the timing of bond issuances, thereby enhancing the comprehensiveness of our analysis. Considering that reported CO_2 emission data in the Vulcan database are only available through 2021, we addressed the gap in data for the 3 year shift corresponding to bonds issued in 2019 by utilizing emission figures from the preceding year. This approach introduces a potential bias, which warrants cautious interpretation and should be evaluated in future studies when more recent emission data becomes available. Furthermore, the control variables, which are time-series data, have been aligned with the emission data at the county level for each respective year.

Data for causal learning are partitioned into training and test sets with an 80:20 ratio to prevent overfitting and to accurately assess the treatment effect. The first stage of model fitting is critical to addressing overfitting; therefore, we employ a search algorithm to identify the optimal estimator for the initial predictive models for both the outcome and the treatment. In the first stage of the analysis, we compared Lasso regression, random forest, and gradient boosting regression to determine the most effective method for predicting emissions and green bond volumes using the confounding variables as predictors. Additionally, we employed a grid search technique to optimize the hyperparameters of each model and enhance the precision of the predictions. To estimate the treatment effect, we applied

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the EconML Python package for the estimation of the treatment effect based on CausalForestDML.[39]

Our approach incorporates a 3-fold cross-validation for all model selection procedures and a grid search strategy for hyperparameter optimization. For the final stage estimation, we utilized the CausalForestDML model for estimating both treatment effects. This involves implementing a causal forest consisting of 1000 trees, utilizing a heterogeneity score as the criterion for splitting nodes. The configuration includes a minimum leaf sample size of 20 and a maximum tree depth of 20. Given the tendency of machine learning models to overfit and potentially skew results, we conducted an examination using an out-of-sample assessment. The relatively small difference in mean square error between the training and test sets indicates that the model is robust against overfitting, as shown in Table 2.

Table 2. Performance Evaluation of the Causal ML Model[a]

	treatment effect$_{t+1}$	treatment effect$_{t+2}$	treatment effect$_{t+3}$
train	0.297	0.304	0.311
test	0.312	0.296	0.278

[a]Mean square error estimated based on the CausalForestDML embedded function "score". $t + n$ indicates a shift of n years when aligning carbon emission data with bond issuance data.

3.2. Impact of Bond Issuance on Carbon Emissions (CATE).

We begin our analysis by assessing the importance of confounders in measuring the treatment effect of the green bond volume on emissions. Figure S3 in the Supporting Information is a Shapley additive explanations (SHAP) summary plot, which elucidates the relative importance of input variables influencing the treatment effects.[40] This method, derived from game theory principles, facilitates a nuanced interpretation of feature importance within the framework of a machine learning model.[41] The variables are arranged in descending order of their importance on the y axis, while the Shapley values are displayed on the x axis. High and low feature importance is indicated by red and blue colors, respectively. Each dotted line represents an observation for a particular feature. A low value (blue dot) for average establishment size has a strong negative impact on the model's output (left side of the x axis). This indicates that counties with a low average establishment size have increased effectiveness of green bonds in reducing emissions. The results indicate that the average establishment size, payroll per employee, GDP, and education level are the predominant variables influencing the effectiveness of green bonds in reducing emissions. The inclusion of use of proceeds (e.g., water, energy, and mass transit) as a confounder was insignificant. This null result is consistent with the literature showing that green bonds often operate through issuer-level signaling or broader organizational commitments rather than exclusively through narrowly targeted project-level effects (13).

The point estimates of ATE for the lagged effect of green bond issuances on CO_2 emissions are shown in Table 3. We find that green bond issuance is associated with statistically significant reductions in local carbon emissions in the subsequent 3 years. The increasing magnitude over time is consistent with implementation delays for financed projects and suggests that emission benefits accumulate as projects reach operation. For example, the 2 year lag ATE of −0.039 (both the treatment and the outcome are in natural logs)

Table 3. ATE Estimates for Green Bond Effectiveness on Emission Reductions[a]

	treatment effect$_{t+1}$	treatment effect$_{t+2}$	treatment effect$_{t+3}$
	A: Causal ML		
ATE	−0.038*	−0.039**	−0.047*
ATE standard error	0.021	0.023	0.025
p value	0.077	0.086	0.065
95% confidence interval	[−0.079, 0.004]	[−0.084, 0.006]	[−0.097, 0.003]
	B: OLS Regression		
	−0.040**	−0.040**	−0.044**

[a]*, $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$. Standard error measures the sampling variability of the treatment effect estimate but does not capture the model's overall predictive error. OLS coefficients and the ATE for the $t + 3$ period use imputed 2022 CO_2 emissions because the Vulcan data set is available only through 2021. The ATE for the causal ML model changes to −0.05** when the 2022 data are removed, and the OLS regression coefficient becomes 0.041** when the 2022 data are removed.

implies an elasticity: a 1% increase in green bond issuance is associated with a 0.039% decrease in CO_2 emissions. For a representative county in our sample, where 1% of the sample mean issuance equals \$184 400, this elasticity implies an annual reduction of roughly 958 tons of CO_2 2 years after issuance, with the implied cost of abatement being \$192 per ton of CO_2. The baseline OLS results in part B show a very similar sign, magnitude, and statistical significance, which increases confidence in the finding that green bond financing is followed by measurable emission declines. The DML estimates are modestly smaller in magnitude for the 1 and 2 year lags, while the 3 year estimate is less consistent. The slight attenuation is consistent with prior literature showing that ML causal estimators (by flexibly modeling functions, regularizing noisy signals, and averaging heterogeneous effects with weights) often produce more conservative and less biased average treatment effects than parametric regressions that impose linearity.[42] Additionally, emissions in one county may be influenced by neighboring counties' policies or economic activity. To test this, we augmented the spectra of the OLS with spatially lagged covariates. The spatially augmented OLS produced only a small improvement in fit, and none of the spatial-lag coefficients were statistically significant (results in Table S1). Given the modest performance gains and the lack of significant lag effects, we did not incorporate spatial clustering into the causal ML pipeline in this study.

The effectiveness of green bonds in reducing carbon emissions exhibits considerable geographic heterogeneity, as illustrated by the individual CATE values shown in Figure 2, which cover issuances from 2009 to 2019 (empty grids do not have any green bond issuance in our study period). Spatial variations in the effectiveness of green bonds on carbon reduction are evident, with the most significant mitigation effects (darkest colors) predominantly observed in California and Washington. While these spatial patterns could reflect differences in regional policy environments (for example, the presence of carbon-pricing programs), formally attributing the heterogeneity to such policies requires explicitly incorporating policy indicators into the empirical specification; we defer that extension to future work. The expected effectiveness of carbon

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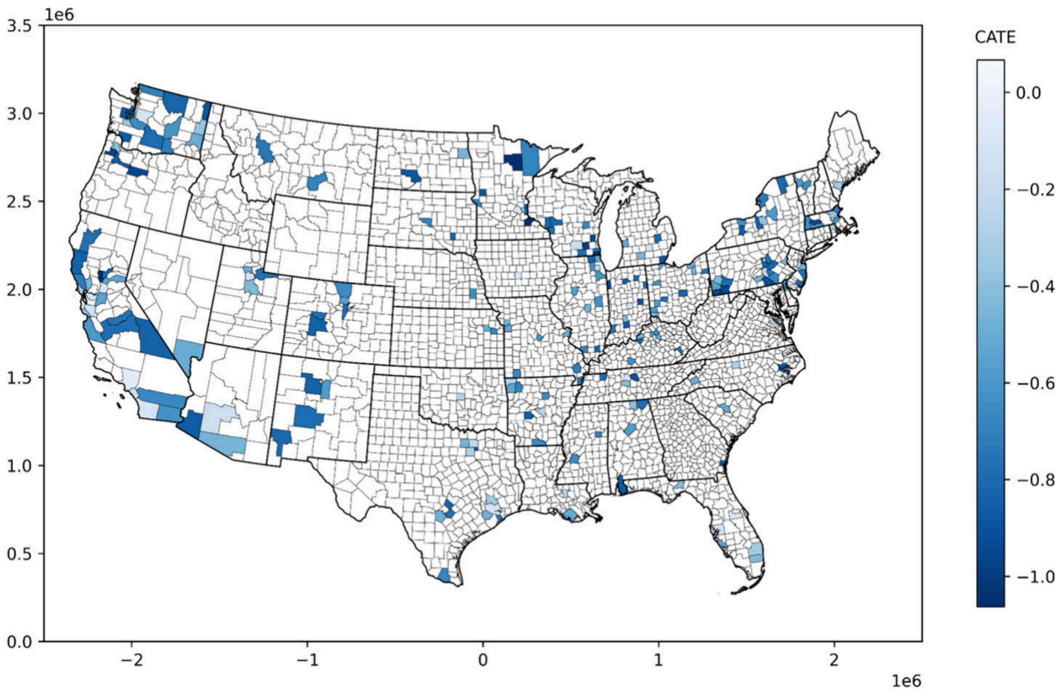

Figure 2. Individual treatment effect of green bond impact on the CO_2 emission in our bond universe.

reduction in regions that have not previously issued green bonds is examined in section 3.5.

The causal tree structure (Figure 3) is utilized to examine the heterogeneity effect in carbon reduction across subgroups of bond issuances when all features are taken into account in the model. It splits the tree based on feature values that maximize the difference in treatment effects between leaves. To aid in the interpretation of tree models, we have limited the maximum tree depth to 2 following previous research.[43] The results identify payroll per employee as the primary driver of heterogeneity in treatment effects for carbon reduction, followed by the average establishment size. For a 1 year lagged effect, for instance, carbon reduction proves to be most effective in counties where the payroll per employee is less than \$55 188 and average establishment size is less than 8.05 employees.

This subgroup exhibits a treatment effect of −0.077, indicating that a 1% increase in green bond issuance is associated with an expected reduction of 0.077% in carbon emissions. To illustrate this, considering an additional investment of \$10 million in green bonds in a county that currently holds \$10 million in green bonds (thereby doubling the original green bond volume) and given that the baseline emission level is 2.5 million tons of CO_2, this increase in green bond investment would lead to a decrease in CO_2 emissions by 192 500 tons 1 year post bond issuance. In contrast, counties with higher payroll per employee (greater than \$55 188) and larger average establishment size (greater than 7.95 employees) demonstrate the lowest impact on CO_2 emission reductions when issuing a higher volume of green bonds. Counties with a low payroll per employee and a small average establishment size likely have a different economic composition than those with larger, high-wage businesses. This structure often consists of numerous small- and medium-sized enterprises (SMEs) or is more rural and agricultural. These businesses may lack the capital and expertise to independently invest in significant carbon reduction technologies. As a result, green bond financing can act as a crucial catalyst, enabling a wide range of smaller scale, high-impact projects.[43]

3.3. Forecasting Green Bond Carbon Reduction Impact. The finding that green finance issuance appears to be more effective at reducing emissions in counties with lower payroll per employee and smaller average establishment sizes has important policy implications. Because urbanization and economic growth will change those socio-economic distributions over time, it is sensible to ask whether the future effectiveness of green finance can be forecast from projected shifts in these key features. Causal ML methods are well-suited to that task: by estimating CATEs as functions of observable covariates and then simulating those CATEs under alternative socio-economic scenarios. Prior work, for instance, has applied causal machine learning methods to predict agricultural land suitability, typically using temperature distributions to estimate heterogeneous treatment effects.[26,43−46]

The two panels in Figure 4 show clear heterogeneity in estimated treatment effects: counties with a lower payroll per employee and a lower GDP level tend to exhibit larger (more negative) CATEs for CO_2 emissions, suggesting that green bond issuance is associated with proportionally larger reductions in those places. These relationships could be used to generate forward-looking scenario forecasts. For example, one could estimate smooth conditional effect functions of payroll and county-level GDP and then evaluate those functions on projected covariate distributions under alternative socioeconomic scenarios (e.g., different trajectories of wage growth, firm consolidation, or urbanization). Aggregating the resulting county-level CATEs, weighted by projected population or economic exposure, would yield scenario-level expected emission reductions. We note that lower payroll per employee may partly proxy for sectoral composition (for instance, a larger share of labor-intensive, less capital- or technology-intensive industries), which might help explain the heterogeneity. Future work could formally test this mechanism

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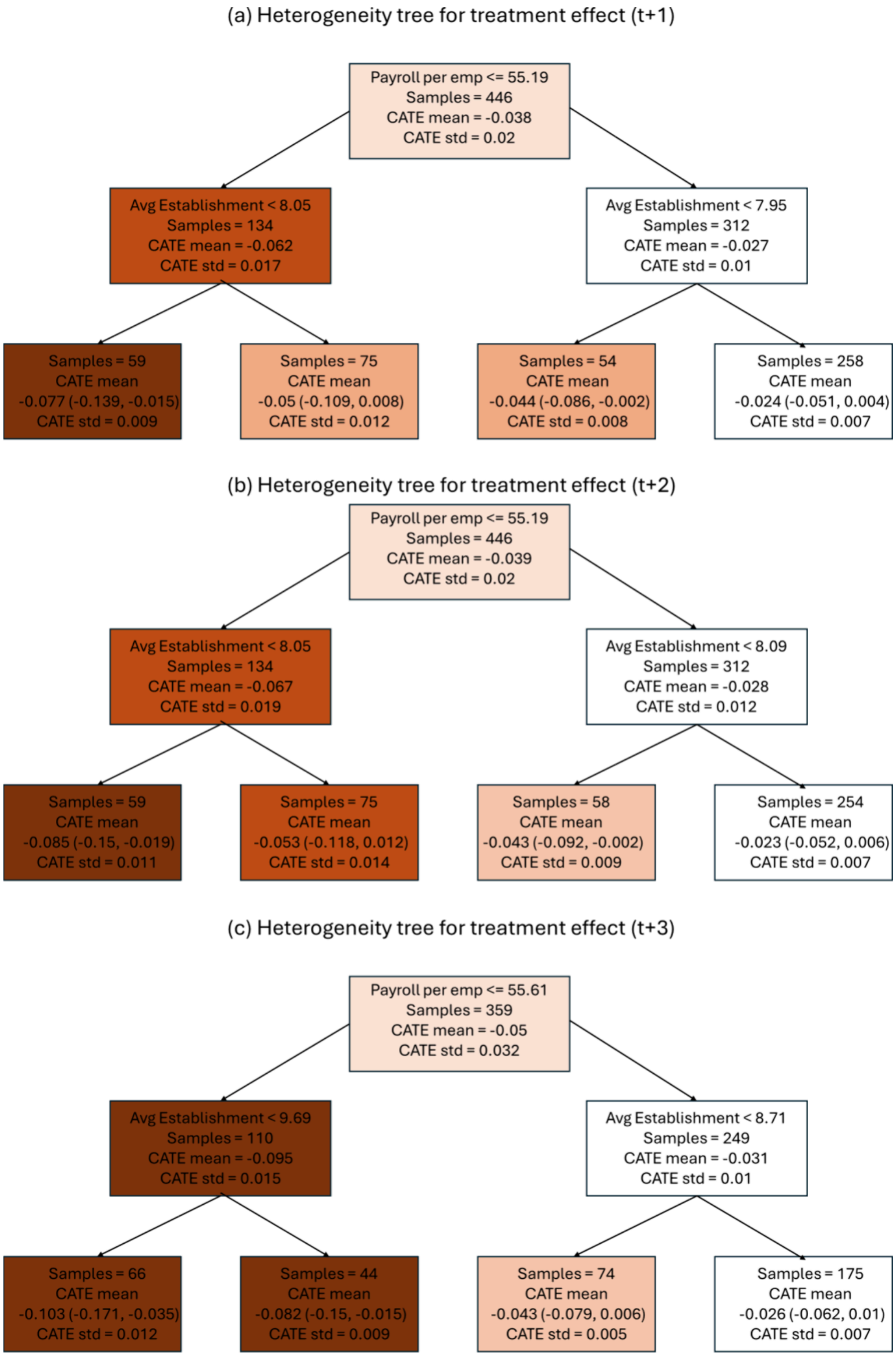

Figure 3. Segmentation of CATE in a tree structure (darker shades denote higher effectiveness).

by including industry controls, interactions with sectoral composition, and alternative proxies for technological intensity.

3.4. Role of Green Certification. Previous literature has not reached a consensus on whether third-party certification materially increases the environmental effectiveness of green bonds. Several studies find that external verification improves credibility and can be associated with larger "green premia" or stronger environmental outcomes, while other work finds limited or context-dependent effects.[11,23,47,50] To explore this question in the municipal market, we screened Bloomberg municipal bond records to distinguish bonds with third-party assurance (coded "yes" for verification) from self-labeled green bonds. While self-labeled green bonds are prevalent, certified green bonds are primarily concentrated in major metropolitan areas (Figure 1).[8]

Using our causal ML framework, we estimate CATEs separately for the certified and self-labeled subsamples. Table 4 reports negative CATEs for both groups, indicating an association between green issuance and subsequent CO_2 reductions, but the two subsamples do not show large differences in magnitude. The between-group contrast is not statistically significant in our tests (Table 4), yet the certified sample is small (N = 67) and geographically concentrated; therefore, these tests have limited power and may be sensitive

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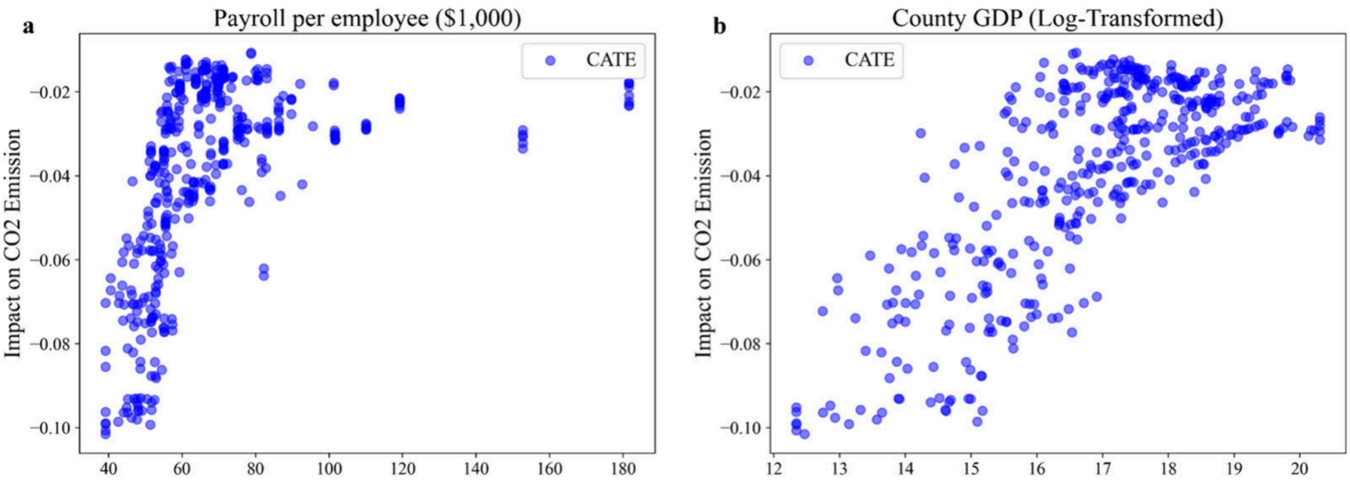

Figure 4. Green bond effectiveness against (a) payroll per employee and (b) GDP level.

Table 4. Estimates of CATE for the Impact of Green Certification on Emission Reductions[a]

	treatment effect$_{t+1}$	treatment effect$_{t+2}$	treatment effect$_{t+3}$
CATE (certified)	−0.036	−0.037	−0.044
	(0.018)	(0.022)	(0.025)
CATE (self-labeled)	−0.038	−0.040	−0.048
	(0.021)	(0.023)	(0.032)

[a]The standard deviation for the "CATE" values of both the certified and self-labeled groups is shown in parentheses. The certified sample size is 67.

to unobserved heterogeneity. For these reasons, we treat the subgroup results as inconclusive and, therefore, refrain from making strong causal claims about the certification's general effectiveness. Future work with larger, more geographically diverse samples of certified bonds or with research designs that better address selection will be important for determining whether and when certification materially increases the climate impact of green municipal bonds.[50]

3.5. Carbon Reduction Impact Inference for First-Time Green Bond Issuers. Given the heterogeneous green bond relationships, we sought to assess the feasibility of projecting the carbon emission impact of first-time green bond issuers. An additional test was conducted using green bond issuance at the county level as a binary treatment variable, considering that a majority of U.S. counties have never issued green bonds in the past (Figure 1). The data set consists of 37 716 county−year observations, with 468 instances of green bond issuances serving as the treatment units. Using the same causal ML model, the ATE estimates from this projection on emission reduction were found to be less significant compared to those from the green bond universe alone. Although the average point estimates of the treatment effects are larger than those for the green bond volume as a continuous variable (section 3.2), the broad distribution of the treatment effects diminishes the significance of the impacts. Nevertheless, as Allman and Lock[48] indicated, the large p value indicates a wide range of variability in the impact of projected green-bond-initiated carbon emission reductions.[49] The findings also reveal that the 2 year lagged effect exhibits the lowest p value, indicating the highest level of statistical significance (Table 5).

Spatial variation in the impact of green bond issuance on emissions is also evident. As illustrated in Figure 5, most regions show carbon reduction effects (indicated in blue, with darker shades denoting greater effectiveness) when issuing green bonds compared to regions without such issuance. However, according to our estimation model, there are regions where green bond issuance is associated with increased emission levels, which are indicated in orange. While we note that the lower significance of ATE results of the model may have resulted in artifacts in the projection that cannot be fully explained by causal inference alone, the higher emissions in counties issuing green bonds may result from an imbalance between economic development activities and low carbon policies.[50]

3.6. Implications for Green Finance Policy and Practice. Climate finance has emerged as a vital instrument for addressing the multifaceted challenges posed by climate change, as it directs large-scale investment toward societal and

Table 5. ATE Estimates for Green Bond Issuance on Emission Reductions[a]

	model 1	model 2	model 3
	treatment effect$_{t+1}$	treatment effect$_{t+2}$	treatment effect$_{t+3}$
ATE	−0.117	−0.093	−0.073
standard error mean	0.181	0.060	0.096
p value	0.519	0.122	0.450
95% confidence interval	[−0.472, −0.238]	[−0.212, 0.025]	[−0.262, 0.116]
number of observations	37716		
number of treatment	468		
number of control	37248		

[a]*, $p < 0.1$; **, $p < 0.05$; and ***, $p < 0.01$.

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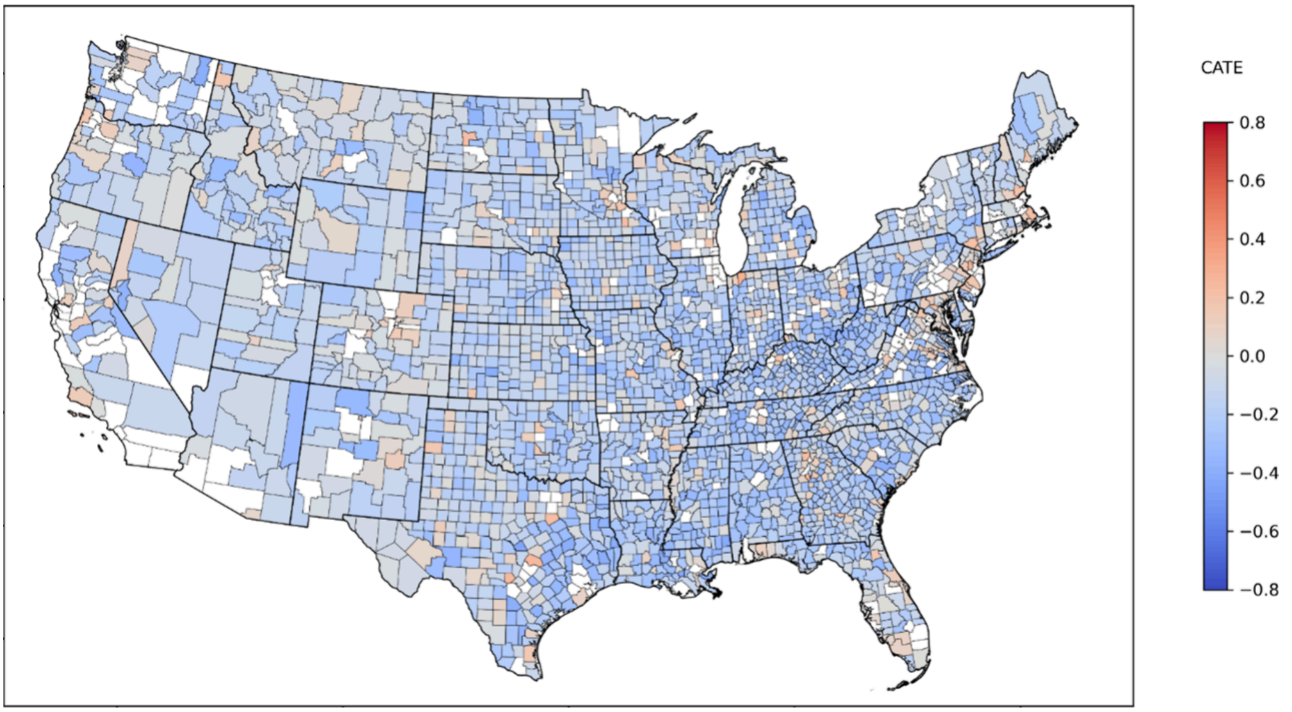

Figure 5. Individual treatment effect of green bond issuance on CO_2 emission based on model 1 from Table 5. The 1 year lagged effect on carbon emission has the largest ATE; therefore, it is being used for visual presentation. The blue color signifies a negative impact of green bond issuance on carbon emissions, indicating reductions, while the orange color denotes a positive impact, indicating increases in emissions. Empty grids indicate either the absence of necessary socio-economic data for estimation or the historical issuance of bonds, rendering the effects of new issuances irrelevant.

environmental initiatives that potentially yield impactful outcomes. While financial investments have increasingly been aligned with sustainable development goals, this study offers a novel perspective by examining the heterogeneity of impacts arising from U.S. green municipal bonds. Employing causal machine learning models, we investigate how increased green bond issuance influences county-level carbon emissions. Our findings reveal significant geographic heterogeneity: the largest emission reductions are concentrated in specific regions and strengthen over time. Counties with a high share of small and medium businesses exhibit the largest emission reductions following green finance interventions, consistent with the idea that green finance can act as a catalytic source of public and private investment. By contrast, certified green bonds, those with independent third-party verification, are not associated with systematically larger emission-reduction effects than self-labeled green bonds in our sample. Furthermore, first-time issuances appear to generate measurable environmental benefits, albeit with wide regional variation.

The approach taken here has limitations, in part due to the size of the green bond and temporal carbon emission data universe and in part due to inherent bias in the methods applied. Despite a significant data set of 8703 municipal green bonds (spanning over 400 counties), the relative novelty of the green bond market constrains our ability to detect robust treatment effects. In addition, attempts to correlate specific uses of proceeds (e.g., water or energy) with emission reductions were inconclusive due to sample size limitations, thus precluding definitive recommendations on project-type allocations. Although we aimed to address the biases and limitations inherent in regression and ATE methods by employing causal machine learning techniques, the potential for selection bias remains. To more rigorously establish causal relationships, advanced methods, such as instrumental variables, may still be necessary.

Opportunities for forward-looking green finance at the county level are multifold and should be guided by the heterogeneity that we observe. First, targeting green bond issuance to counties with lower payroll per employee, smaller average establishment sizes, or lower GDP level, where our estimates show the largest CO_2 reductions, may increase cost-effectiveness. Regions with specific socioeconomic profiles remain important candidates for tailored interventions, but the expected impacts will vary across places and over time. Second, urban planning and zoning decisions should explicitly incorporate green investment strategies to ensure that urbanization trajectories do not dilute the intended environmental gains. Third, issuer-level heterogeneity likely reflects differences in governance, administrative capacity, and local tax bases that affect how green bonds are deployed and monitored; these institutional factors should inform allocation and technical-assistance decisions. Fourth, our analysis finds no clear, general advantage for third-party certification in municipal bonds within the available sample; therefore, policymakers should weigh certification's credibility benefits against its costs and the current lack of conclusive evidence on incremental climate impact. Finally, because spatial heterogeneity and regional interdependence are present, scenario-based forecasting that projects covariate distributions (e.g., wages, firm structure, and urbanization) and simulates conditional treatment effects can help prioritize counties and design more effective, place-sensitive green finance policies while acknowledging substantial uncertainty and the need for further spatially explicit causal research.

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■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.5c04966.

Additional figures, such as the sectoral decomposition of county-level carbon emissions, correlation matrix of variables, feature importance for treatment effect estimation, and robustness tests on spatial lag effects (PDF)

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Notes

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