Birds, Wells, and Turbines: A Replication of Katovich (2023)

Reevaluating the Causal Effects of Energy Infrastructure on U.S. Bird Populations

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1 Introduction

The expansion of energy infrastructure has raised concerns about its impact on wildlife. In *Quantifying the Effects of Energy Infrastructure on Bird Populations and Biodiversity*, Katovich (2023) examines the ecological consequences of two major U.S. energy technologies—shale oil and gas (fracking) and wind energy. Using data from the Audubon Society's Christmas Bird Count (CBC) and infrastructure registries from 2000 to 2020, the study finds that bird abundance declines significantly near shale wells, while wind turbines have no measurable effect.[1]

The central question in Katovich (2023) is whether shale wells and wind turbines causally impact bird abundance and species diversity. To address this, he uses a staggered difference-in-differences (DiD) framework with the `csdid` estimator, which accounts for treatment timing heterogeneity across geographic units. The design compares bird counts before and after infrastructure arrival, controlling for fixed characteristics and time-varying factors such as weather, land use, and survey effort.

In this essay, I replicate Katovich's analysis using a similar dataset and a classical two-way fixed effects DiD specification. I begin by discussing the key assumptions of the DiD model and assessing the reliability of the resulting estimates. Then, I estimate the effects of both the arrival and intensity of energy infrastructure using binary and continuous treatment DiD specifications. To strengthen my findings, I conduct robustness checks, implement placebo tests, and use visualizations and event studies to assess the parallel trends assumption and support a more transparent causal analysis.

2 Data and Identification Strategy

2.1 Data

This study uses longitudinal panel data from the CBC, a nationwide bird survey conducted annually within fixed, specific circles across the contiguous United States. Trained volunteers systematically record bird counts by species, along with effort-related and environmental variables such as observer numbers, method, temperature, snowfall, and wind speed. The CBC's consistent protocol and stable circle locations from 2000 to 2020 reduce measurement error and support credible temporal comparisons, and lays a foundation for causal inference.

[1] For background on the policy relevance and related literature, see Katovich (2023), Sections 1 and 2.

To define each circle's spatial domain and prevent overlap, Voronoi polygons[2] are used to partition space such that each area is assigned to its nearest CBC circle. Within these domains, treatment is defined using a 5-km buffer around each circle to capture exposure to nearby energy infrastructure while minimizing spillovers between treated and untreated units. These infrastructure records include precise installation dates and locations, allowing for accurate temporal and spatial matching. To account for other possible sources of variation, the dataset includes additional covariates that vary across time and space, such as land cover composition (e.g., agriculture, developed land), human population, and local weather. These controls help address potential confounding due to concurrent environmental or human activities.

2.2 Identification Strategy

This structure supports a DiD panel strategy that tracks bird populations within each location before and after nearby energy infrastructure appears. Circle fixed effects control for all time-invariant location characteristics, while year fixed effects absorb nationwide shocks. Unlike standard OLS, DiD does not require a strict exogeneity assumption; instead, identification relies on a weaker, design-based condition: the unconditional parallel trends assumption—that in the absence of treatment, treated and control units would have followed similar outcome trajectories. By additionally controlling for time- and space-varying covariates—such as land cover, weather, population, and survey effort—I invoke a conditional version of the parallel trends assumption, further reducing the risk of omitted-variable bias. DiD thus enables causal inference by leveraging repeated observations and staggered treatment timing, rather than relying on orthogonality between treatment and unobservables.

This empirical strategy is well-positioned to support causal inference, conditional on a set of assumptions that are either tested empirically or justified through design-based reasoning. Visual inspection of parallel pre-trends, along with event-study estimates, will assess whether treated and control circles followed similar trajectories prior to treatment and whether anticipatory effects are present. Circle and year fixed effects, combined with time-varying controls for land cover, weather, population, and survey effort, help mitigate omitted-variable bias. Spillovers are minimized through 5-km buffers and wide spatial spacing; placebo rings can provide additional checks for residual interference. Measurement error is limited by the CBC's standardized protocols, and reverse causality is

[2] A Voronoi polygon assigns each location in space to the nearest reference point (in this case, a CBC circle), creating non-overlapping zones based on proximity.

unlikely given the long permitting timelines for infrastructure and the fixed timing of bird surveys. Together, these design elements and empirical diagnostics support a credible causal interpretation of the estimated DiD effects.

However, I do not implement the Callaway & Sant'Anna (2021) csdid estimator used in the original analysis, so our two-way FE estimates may still suffer from heterogeneous, staggered-treatment bias. External validity is also limited—CBC circles aren't a random draw of U.S. habitats—but, as Katovich (2023) emphasizes, the CBC's uniform protocols, nationwide coverage, and two-decade panel deliver far more powerful insights than earlier, localized studies.

3 Specification and Main Results

3.1 Specification

To estimate the effect of nearby energy infrastructure on bird populations, I use both binary and continuous DiD models, including circle and year fixed effects. Treatment is defined either as the first arrival or the cumulative intensity of shale wells or wind turbines within a 5 km buffer around a CBC circle. Models are estimated separately for each type of infrastructure.

The dependent variable is the inverse hyperbolic sine (IHS) of total bird counts. Given that it behaves similarly to a log transformation at moderate to large values while preserving zero observations—and that most circles report high counts (median ≈ 8,000)—coefficients can be interpreted approximately as percent changes.[3]

The binary-treatment specification is presented in Equation 1:

$$\text{IHS(BirdCount)}_{it} = \alpha + \delta \cdot \text{Post}_{it} + \mu_i + \lambda_t + \mathbf{X}_{it}\beta + \varepsilon_{it} \tag{1}$$

Here, Post_{it} switches on in the first treatment year, while μ_i and λ_t are circle and year fixed effects, respectively. Our coefficient of interest, δ, measures the average percent change in bird counts when treatment switches from 0 to 1 (semi-elasticity).[4]

The vector $\mathbf{X}_{it}$ includes a set of time-varying controls chosen based on their predictive value,

[3]For small values or larger effects, exact semi-elasticities can be computed as $100 \cdot (e^{\beta} - 1)$.

[4]Bellemare, M. F. & Wichman, C. J. (2020). "Elasticities and the inverse hyperbolic sine transformation," *Oxford Bulletin of Economics and Statistics*, 82(1), 50–61.

balance with respect to treatment, and potential to bias the estimated treatment effect if omitted. Volunteer effort, measured by the total number of observers, is a key covariate: it declines after shale exposure and positively predicts bird counts, so omitting it biases δ downward. Core weather variables—minimum and maximum temperature, maximum wind, and snowfall—are retained because they improve precision, though they are orthogonal to treatment. Other weather controls (e.g., cloud, rain, and categorical snow measures) show little explanatory power and are excluded to preserve sample size. Still water indicators are included when feasible; although unrelated to treatment, they significantly raise bird counts, likely due to improved detectability or habitat quality in winter. Land-use shares (agriculture, pasture, developed) vary little over time and are soaked up by fixed effects; they are retained only in robustness checks. Party-hours[5] are excluded due to frequent recording errors and no systematic shift post-treatment.

The continuous-treatment specification, shown in Equation 2, replaces the binary indicator with the IHS of cumulative wells, turbines, or production within 5 km of each CBC circle. Since treatment variables are highly right-skewed with many zeros, the IHS transformation helps retain all observations while compressing extreme values. Our coefficient of interest, δ, measures the percent change in bird counts for a one-percent change in treatment intensity (elasticity).[6]

$$\text{IHS}(\text{BirdCount})_{it} = \alpha + \delta \cdot \text{IHS}(\text{Treatment})_{it} + \mu_i + \lambda_t + \mathbf{X}_{it}\beta + \varepsilon_{it} \tag{2}$$

Standard errors are clustered at the circle level, which reflects the level of treatment assignment and accounts for serial correlation in repeated measures within each observational unit over time. This ensures valid inference and hypothesis testing in the presence of within-cluster dependence.

3.2 Results

Taken together, the regression results in Tables 1 and 2 provide evidence of a negative causal effect of shale development on winter bird abundance, under the identification strategy established earlier. In the binary DiD model (Table 1), the estimated post-treatment decline is $\delta = -0.113$ (SE $= 0.087$; $p = 0.196$), corresponding to an approximate 11.3% drop in bird abundance following the first well's

[5] Party-hours combine observer count and time in the field but are sometimes recorded as zero despite positive bird counts. Cleaning these inconsistencies substantially reduces the sample and increases variance. Since party-hours do not shift systematically post-treatment, they are excluded from the preferred specification.

[6] Bellemare, M. F. & Wichman, C. J. (2020). "Elasticities and the inverse hyperbolic sine transformation," *Oxford Bulletin of Economics and Statistics*, 82(1), 50–61.

arrival, with a within-R^2 = 0.0497. In contrast, the continuous-treatment estimates (Table 2) reveal a statistically significant dose–response: a 10% increase in cumulative shale production is associated with a 0.68% decline in bird counts ($\delta = -0.0678$, SE = 0.0218; $p = 0.002$; within-R^2 = 0.0528), and this result holds under state×year fixed effects ($\delta = -0.0636$, SE = 0.0222; $p = 0.004$; within-R^2 = 0.1128). Although modest in magnitude, this effect accumulates with large-scale development and is directionally consistent with prior findings. Across all models, wind turbines show no measurable impact on bird abundance, with small and statistically insignificant coefficients (e.g. $\delta = 0.0066$, SE = 0.0348; $p = 0.850$).[7]

While identification relies on a conditional parallel-trends assumption (controlling for fixed effects and time-varying covariates), standard two-way fixed effects (TWFE) can mis-handle heterogeneous treatment effects across space and time. Without estimators like `csdid`[8] , TWFE comparisons of early-, late-, and never-treated units may violate conditional trends or use inappropriate weights. If treatment effects evolve or vary by timing and intensity, TWFE can produce attenuation bias or inefficiency—especially in the binary model, where all treated units are pooled post-treatment. By contrast, the continuous specification preserves more exposure variation, and its robustness under stricter controls suggests it better captures the true pattern of effects.

[7] Within-R^2 values are low because fixed effects absorb most cross-sectional variation and treatment variation is relatively rare and localized; this does not compromise the unbiasedness or precision of our DiD estimates.

[8] See Callaway and Sant'Anna (2021), "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, and Sun and Abraham (2021), "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*.

Table 1:
Binary TWFE DiD Estimates of Shale and Wind Effects on Bird Counts
(2000–2020, U.S. Audubon CBC circles)

	IHS(total bird counts)		
	(0) Baseline	(1) Core Specification[a]	(2) Extended Controls[b]
Shale treatment	−0.1345	−0.1130	−0.1134
	(0.0901)	(0.0872)	(0.0873)
	[0.136]	[0.196]	[0.194]
Control bundle 1	No	Yes	Yes
Control bundle 2	No	No	Yes
Fixed effects (circle & year)	Yes	Yes	Yes
Wind turbine treatment	0.0086	0.0066	0.0063
	(0.0350)	(0.0348)	(0.0348)
	[0.805]	[0.850]	[0.855]
Control bundle 1	No	Yes	Yes
Control bundle 2	No	No	Yes
Fixed effects (circle & year)	Yes	Yes	Yes
Method	Binary DiD	Binary DiD	Binary DiD
Observations	30,336	30,336	30,336
Within R^2	0.0271	0.0497	0.0515

[a] adds Control bundle 1 (weather & survey effort).

[b] adds Control bundle 2 (land-use shares & still-water dummy) for greater precision.

Notes: ( ) = robust standard error clustered at the circle level; [ ] = p-value.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *No coefficients in this table are statistically significant at conventional levels.*

Control bundle 1: minimum temperature, maximum temperature, maximum wind speed, maximum snow depth, total survey effort.

Control bundle 2: agricultural & pasture land share, developed land share, still-water dummy.

Table 2:
Continuous TWFE DiD Estimates of Shale Wells, Shale Production, and Turbine Intensity on Bird Counts (2000–2020, U.S. Audubon CBC circles)

	IHS(total bird counts)			
	(0) Baseline	(1) Core Specification[a]	(2) Extended Controls[b]	(3) State-Year FE Robustness[c]
IHS(cumulative shale wells)	-0.0551^{***}	-0.0499^{***}	-0.0504^{***}	-0.0457^{***}
	(0.0167)	(0.0159)	(0.0159)	(0.0160)
	[0.001]	[0.002]	[0.002]	[0.004]
Control bundle 1	No	Yes	Yes	Yes
Control bundle 2	No	No	Yes	Yes
State×Year interactions	No	No	No	Yes
Fixed effects (circle & year)	Yes	Yes	Yes	Yes
IHS(cumulative shale production)	-0.0749^{***}	-0.0678^{***}	-0.0681^{***}	-0.0636^{***}
	(0.0229)	(0.0218)	(0.0218)	(0.0222)
	[0.001]	[0.002]	[0.002]	[0.004]
Control bundle 1	No	Yes	Yes	Yes
Control bundle 2	No	No	Yes	Yes
State×Year interactions	No	No	No	Yes
Fixed effects (circle & year)	Yes	Yes	Yes	Yes
IHS(cumulative turbines)	0.0028	0.0048^{*}	0.0048^{*}	0.0033
	(0.0137)	(0.0135)	(0.0135)	(0.0129)
	[0.838]	[0.722]	[0.722]	[0.799]
Control bundle 1	No	Yes	Yes	Yes
Control bundle 2	No	No	Yes	Yes
State×Year interactions	No	No	No	Yes
Fixed effects (circle & year)	Yes	Yes	Yes	Yes
Method	Continuous DiD	Continuous DiD	Continuous DiD	OLS DiD with State–Year FE
Observations	30,336	30,336	30,336	30,336
Within R^2	0.0285	0.0509	0.0528	0.1128

[a] Adds Control bundle 1 (weather & survey effort).
[b] Adds Control bundle 2 (land-use shares & still-water dummy).
[c] Difference-in-Differences (OLS) with state-by-year fixed effects to relax parallel-trends.
Notes: ( ) = robust SE clustered at circle level; [ ] = p-value.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Control bundle 1: minimum temperature, maximum temperature, maximum wind speed, maximum snow depth, total survey effort.
Control bundle 2: agricultural & pasture land share, developed land share, still-water dummy.

4 Robustness and Validation Checks

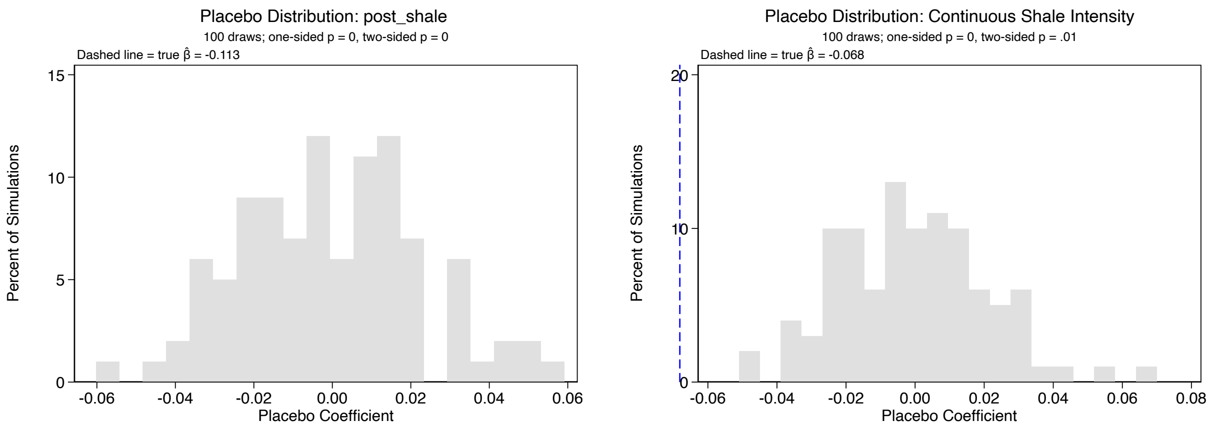
4.1 State–Year Fixed Effects Robustness

As a stricter robustness check, I re-estimate the continuous-treatment model (Eqn. 2) adding state-by-year fixed effects so each state can have its own year-specific trend, thus relaxing the parallel-trends assumption to within each state-year. As shown in the final column of Table 2, the effect of shale remains virtually unchanged—its coefficient moves from -0.050 to -0.046 ($p = 0.004$)—showing it isn't driven by state-level confounders. This specification is feasible only for the continuous-treatment model, since the continuous measure preserves sufficient within-state-year "dose" variation (the number or density of wells) that isn't absorbed by the fixed effects, whereas a binary indicator would leave almost no remaining variation.

4.2 Placebo Tests

To test whether our effects arise by chance, I run 100 placebo draws for each DiD model: in the binary DiD, circles are randomly assigned to treatment (keeping the treated share); in the continuous DiD, each circle is given a donor's IHS(cumulative shale production) path (keeping year structure). Each draw re-estimates its model, producing null distributions of $\hat{\beta}$ (Figure 1). In both panels, the true estimates ($\hat{\beta}_{\text{post-shale}} \approx -0.113$, $\hat{\beta}_{\text{cumulative-shale-production}} \approx -0.068$) lie in the extreme tails ($p \approx 0$), indicating the observed impacts are unlikely under random variation.

Figure 1: Distribution of Placebo Coefficients

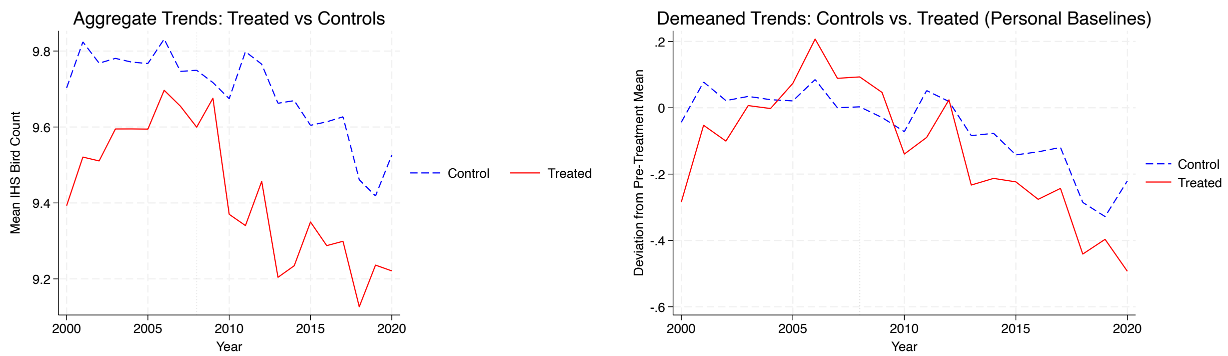


Notes: Each panel plots the distribution of placebo treatment coefficients across 100 randomizations. Left: binary DiD placebo using randomly assigned treatment groups. Right: continuous DiD placebo using randomly reassigned shale production paths. Dashed line indicates the actual estimated treatment effect in the real data. In both cases, the true effect lies far in the tails of the null distribution, yielding one-sided $p \approx 0$.

4.3 Event Study and Aggregate Trend Visualizations

To illustrate trends, Figure 2 plots average IHS bird counts over time for treated and control circles, both raw and demeaned by pre-treatment means. Treated circles show sharper post-treatment declines, but without conditioning on covariates these visuals alone cannot confirm parallel pre-trends.

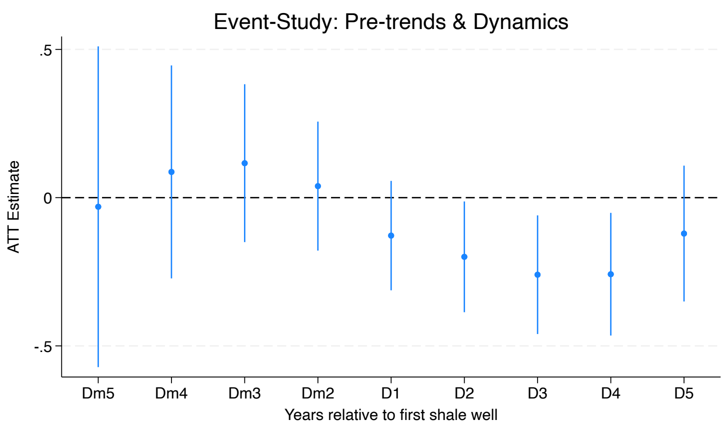
Figure 2: Aggregate and Demeaned Trends: Treated vs. Control Circles



Notes: Left: raw average IHS bird counts by year. Right: trends demeaned by pre-treatment means. Dashed line marks average treatment year. Covariates not adjusted.

Figure 3 presents an event-study regression with circle and year fixed effects plus weather, land-use, and effort controls. All pre-treatment coefficients are jointly insignificant (F-test $p = 0.67$), supporting conditional parallel trends, while post-treatment coefficients indicate a sustained, significant decline in bird counts.

Figure 3: Event-Study: Dynamic Effects of Shale Wells on Bird Abundance



Notes: Coefficients show annual changes in IHS bird counts relative to $t = -1$, estimating the average treatment effect on the treated (ATT). Regression includes circle and year fixed effects plus controls for weather, land-use, and effort. Dashed line at zero effect. All pre-treatment coefficients jointly insignificant (F-test $p = 0.67$).

4.4 Mechanism Check: Human Population as a Mediator

I conducted a mediation analysis to assess whether changes in local human population explain the negative effects of energy infrastructure on bird abundance. This requires two conditions: infrastructure must influence population (first stage), and population must, in turn, affect bird counts (second stage).

Table 3: **Mediation Analysis: Human Population and Land Shares**
(2000–2020, U.S. Audubon CBC circles)

	Coefficient	Std. Error	p-value
First Stage: Effect of Shale Wells on Mediators			
Human Population	-0.020	(0.015)	[0.184]
Agricultural & Pasture Share	-0.005	(0.004)	[0.298]
Developed Share	0.009	(0.010)	[0.394]
Controls			Yes
Fixed effects (circle & year)			Yes
Observations			30,336 per model
First Stage: Effect of Wind Turbines on Mediators			
Human Population	-0.014	(0.006)	[0.015]
Agricultural & Pasture Share	0.002	(0.001)	[0.166]
Developed Share	0.001	(0.007)	[0.880]
Controls			Yes
Fixed effects (circle & year)			Yes
Observations			30,336 per model
Second Stage: Effect of Mediators on Bird Counts			
Human Population	-0.066	(0.105)	[0.529]
Human Population (1yr lagged)	-0.043	(0.116)	[0.712]
Agricultural & Pasture Share	-0.282	(0.184)	[0.125]
Developed Share	0.076	(0.062)	[0.223]
Controls			Yes
Fixed effects (circle & year)			Yes
Observations			30,336 (lagged model: 26,109)
Method			OLS DiD (separate regressions)

Notes: ( ) = Robust SE clustered at circle level, except county level for second-stage human population models. ; [ ] = p-value.
All models include year and circle fixed effects, and control for minimum/maximum temperature, maximum wind speed, maximum snow depth, and total survey effort.
The outcome is inverse hyperbolic sine (IHS)-transformed only in the second-stage regressions for bird counts. Population is in logs.

Our analysis (Table 3) finds little evidence that human population mediates the effect of energy infrastructure on bird abundance. Shale wells have no significant effect on population, and more importantly, population levels do not significantly predict bird counts. Since human-driven impacts may also occur through land conversion, I tested agricultural and developed land shares as alternative mediators. These, too, show no consistent effects. This may reflect a limitation of our data: land shares change slowly over time and may not adequately capture short-term or localized habitat disruption. I also tested for lagged effects of human population on bird counts, but found no significant relationship. Overall, these findings point to more immediate mechanisms—such as noise, light, or direct habitat disturbance—as likely drivers of the observed bird declines.

5 conclusion

This replication of Katovich (2023) confirms that shale oil and gas infrastructure exerts a measurable, negative causal impact on winter bird abundance, while wind turbines remain inconsequential. Our continuous-treatment DiD estimates uncover a robust dose–response relationship—each 10% increase in cumulative shale production yields an approximate 0.68% decline in bird counts—that persists across richer control sets, state–year fixed effects, placebo simulations, and event-study diagnostics. Mediation analyses rule out human population shifts or gradual land-use changes as primary channels, pointing instead toward more immediate disturbances (e.g. noise, light pollution, habitat disruption) as the likely mechanisms. Ultimately, these results call for clear actions and stronger rules to ensure shale development doesn't harm our ecosystems.

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