Assessing Local Economic Effects from Landfill Gas Projects Using Satellite Imagery*

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Abstract

Governments often promote environmental infrastructure as a means to deliver both environmental and economic benefits. Yet whether such projects achieve the promised win-win outcomes remains uncertain. This paper examines the local economic effects of landfill gas-to-energy (LFG) projects in Texas, where such projects have been widely adopted. We assemble an annual panel of census tracts within three miles of landfill sites from 2015 to 2023, combining EPA facility records with satellite-derived nightlights, land-cover classifications, and socioeconomic measures from the American Community Survey. Because LFG facilities are systematically sited at larger and more developed landfills, we construct a matched control panel based on pre-treatment spatial and socioeconomic characteristics and employ staggered difference-in-differences to identify dynamic treatment effects. We find modest increases in built-up area near LFG sites and but no statistically significant changes in household income or employment. These results indicate that while LFG projects deliver environmental benefits, they do not generate measurable economic spillovers for nearby communities. It suggests a gap between green development narratives and observed outcomes, underscoring the need for complementary policies to advance both climate and equity objectives.

JEL Classification: Q52, Q53, R11, C23

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1 Introduction

Environmental infrastructure investments are often promoted as policies that jointly advance environmental and development goals. Recent studies have shown that the green energy transition promises both environmental and economic gains for nearby communities (Jacobson et al., 2017; Wang et al., 2025). Advocates argue that investments in cleaner technologies will reduce harmful emissions while creating local jobs and stimulating local economic activity. In the United States, landfill gas-to-energy (LFG) facilities have been lifted up as an embodiment of this dual promise. As of September 2024, 542 operational projects nationwide convert methane from municipal solid waste landfills into electricity or renewable natural gas (U.S. EPA, 2024b). These facilities are presented as evidence that environmental investments can simultaneously support community development and climate objectives (Banzhaf et al., 2019; Al-Hazmi et al., 2024). Despite these claims, however, empirical evidence on their local economic effects remains scarce.

Understanding the local consequences of these projects is important because landfills are disproportionately located in disadvantaged areas. Communities near landfills tend to have lower incomes, higher minority shares, and weaker institutional capacity (Yandle and Burton, 1996; Mohai, 1996). These facilities also have significant pollution risks, exposing nearby residents to odors and air contaminants (Colmer et al., 2020, 2024). If green infrastructure is expected to transform environmental improvements into local economic opportunity, such gains should be most visible where these facilities operate. Whether LFG projects generate measurable changes in income, employment, or neighborhood composition thus speaks directly to the credibility of the win-win narrative that underpins environmental justice policy.

This paper investigates whether environmental-infrastructure investments generate economic benefits for nearby communities by improvements in local physical or socioeconomic conditions. We focus on LFG projects in Texas, where such facilities have been widely adopted. This question is central to assessing whether green infrastructure delivers broader development dividends beyond its environmental purpose.

The main identification challenge arises because LFG facilities tend to be developed at larger and more urbanized landfills, meaning that treated and untreated tracts differ systematically before project initiation. To address this, we construct a matched control panel that aligns tracts on pre-

treatment socioeconomic and spatial characteristics. The analysis draws on facility-level records from the Environmental Protection Agency's Landfill Methane Outreach Program, combined with satellite-derived measures of nightlight intensity and land-cover classification, and tract-level socioeconomic data from the American Community Survey. Nightlights capture changes in local production and economic activity, while built-up area reflects the accumulation of physical structures such as commercial facilities and roads (Donaldson and Storeygard, 2016; Chi et al., 2022). Together with income, employment, and demographic indicators, these measures provide complementary perspectives on local economic conditions.

Using this integrated panel that captures spatial and economic dynamics across locations, we estimate post-treatment effects with staggered difference-in-differences (Callaway and Sant'Anna, 2021). This approach adapt variation in treatment timing across facilities and provide robustness to differential pre-treatment trends that often challenge standard two-way fixed-effects models. It allows a robust assessment of how local conditions evolve before and after project initiation.

Our findings challenge policy narratives about win-win environmental infrastructure. The results show modest increases in built-up area near LFG sites-on the order of 0.4 to 0.8 percentage points-consistent with limited commercial or infrastructure development in surrounding areas. However, we find no statistically or economically significant changes in household income, employment, or demographic composition. We similarly find no evidence of demographic shifts, suggesting that LFG operations do not trigger changes in neighborhood composition within the observable time frame. The findings indicate that while LFG projects deliver environmental benefits through methane abatement, their local economic impacts are negligible, underscoring the need for complementary policies-such as local hiring or community-benefit agreements.

These results contribute to three ongoing debates. First, our findings suggest that environmental infrastructure does not spontaneously generate local development benefits without intentional policy mechanisms to channel economic gains to host communities. Second, our results indicate that reductions in pollution do not necessarily translate into changes in the spatial distribution of socioeconomic opportunity, a central concern in environmental justice research. Third, our estimations demonstrate the value of satellite-based metrics in detecting localized physical changes that are not visible in administrative socioeconomic data.

2 Related Work

2.1 Empirical Context : Landfill Gas to Energy Projects

Municipal solid waste landfills account for a major share of anthropogenic methane emissions in the United States. The United States sends about 12 percent of the world waste stream to landfills despite accounting for only 4 percent of the global population. This imbalance raises concerns about methane emissions, public health, and fiscal management. In response, policymakers and environmental groups have promoted LFG projects as a practical methane mitigation tool. The EPA estimates that landfills produced roughly one fifth of national methane emissions in recent years, making them the third largest source after the energy and agricultural sectors (U.S. EPA, 2024a). The Landfill Methane Outreach Program is the federal initiative designed to support methane recovery by compiling project level data, providing technical assistance, and facilitating partnerships with private developers.

LFG installations vary across facilities. Some generate electricity through internal combustion engines or turbines, while others upgrade gas for pipeline injection as renewable natural gas. This variation implies that local spillovers are unlikely to be uniform and depend on local market conditions.

Texas provides an informative setting for examining these effects. The state operates one of the largest landfill networks in the United States and has been an active participant in the Environmental Protection Agency's Landfill Methane Outreach Program. 16 LFG facilities opened in Texas between 2013 and 2023, generating staggered treatment timing across diverse geographic and socioeconomic contexts. The state also exhibits substantial heterogeneity in urbanization,allowing comparisons across both metropolitan and peripheral areas. This variation makes Texas a valuable case for assessing whether environmental infrastructure yields local economic spillovers under differing baseline conditions.

2.2 LFG and Environmental Impacts

Prior literatures have documented the economic impacts of renewable energy infrastructure deployment. The transition to renewable energy is promoted not only for environmental benefits but also for crucial socioeconomic advantages, including job creation, income growth, and technolog-

ical spillovers. A comprehensive meta-analysis on renewable energy deployments reveals diverse economic and social effects across different contexts (Brunner and Schwegman, 2022; Jacobson et al., 2017; Virah-Sawmy and Sturmberg, 2025). Commonly observed benefits include increased local employment and investment during both construction and operation phases of renewable facilities, along with longer-term gains from enhanced energy security and reduced pollution costs. However, outcomes vary considerably by context. While some communities experience substantial economic rewards from projects, others see more modest or mixed results, depending on factors such as policy support, project scale, and existing local economic structures. Theoretical frameworks emphasize that projects generate positive externalities, including reduced carbon emissions and health benefits, which can enhance overall welfare when properly internalized through policy mechanisms (Siler-Evans et al., 2013). The literature indicates that renewable energy infrastructure produces net positive economic impacts, particularly when supported by complementary policies designed to maximize local benefits.

2.3 Satellite Based Measures in Socioeconomic Research

Recent research demonstrates both the potential and the limitations of using satellite imagery for economic measurement. A pioneering example is the use of nighttime lights as a proxy for gross domestic product (Henderson et al., 2012). This framework leverages satellite-recorded night lights to augment official growth estimates, demonstrating that lights-based measures can significantly improve estimates for countries with weak statistical systems. In fact, light data allows analysis at finer spatial units. Using satellite night luminosity, researchers can estimate growth at subnational scales, rather than treating entire countries as the unit of analysis (Yeh et al., 2020). The field has expanded considerably beyond nighttime lights in recent years. Higher resolution daytime imagery combined with improved computing power allows analysts to extract diverse socioeconomic indicators directly from satellite photographs. Features visible in daytime imagery such as road networks, building densities, and cropland extent, have been successfully linked to local income and consumption levels, opening new possibilities for economic measurement in data scarce environments (Donaldson and Storeygard, 2016).

3 Data

3.1 EPA LMOP Facility Records

Our treatment variable is derived from the Environmental Protection Agency's Landfill Methane Outreach Program, which documents LFG and energy projects nationwide. For Texas, we identify 16 LFG facilities with verifiable project initiation years between 2013 and 2023. We geocode each facility using its reported coordinates and construct a three-mile Euclidean distance buffer around each location. Census tracts are assigned to treatment if any portion of their geographic area intersects this buffer zone, capturing neighborhoods with potential exposure to facility operations. This spatial assignment yields 1,020 treated tracts.

As shown in Table 1, project openings are distributed unevenly across time, with most activity concentrated in 2018 and 2019 (509 treated tracts), and only a single new facility opening in both 2013 and 2023. Of these facilities, 9 are privately owned and 7 are publicly operated, distributed across 11 counties. Because the ACS and satellite data begin in 2015 with consistent tract geometries, we focus our analysis on facilities that became operational between 2015 and 2023. These treatment years define the staggered timing structure used in the empirical design. We select a three-mile radius to balance capturing localized economic spillovers while maintaining sufficient geographic coverage to detect tract-level changes in our outcome measures.

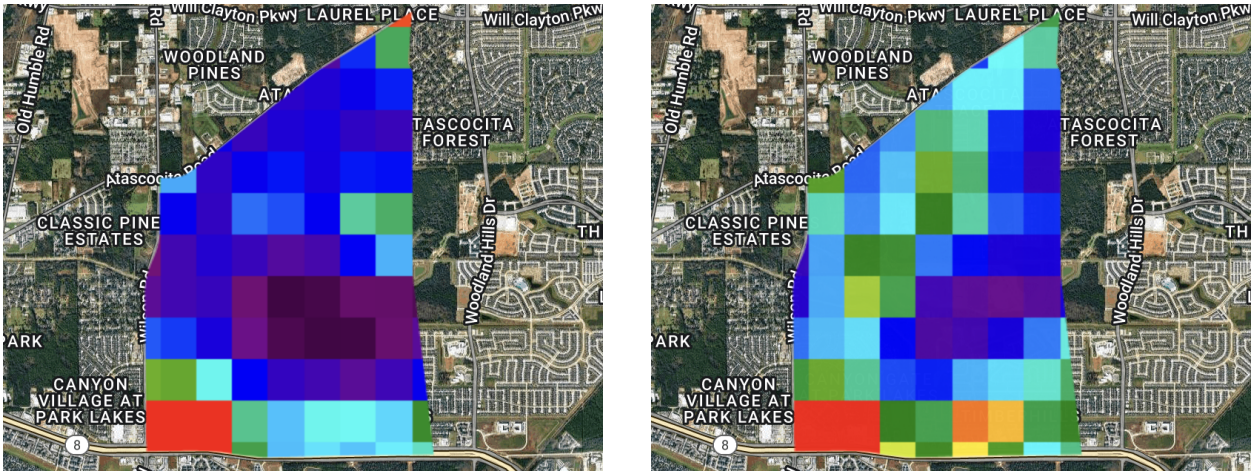
Table 1: Built Year, Landfill Name, Tract Location, and Ownership Type

Built Year	Landfill Name	Tract Name	Ownership Type
2013	Fort Bend Regional Landfill	Census Tract 6756, Fort Bend County	Private
2014	City of Victoria Landfill	Census Tract 17, Victoria County	Public
2014	Nelson Gardens LF	Census Tract 1618.02, Bexar County	Public
2016	City of Edinburg Landfill	Census Tract 235.11, Hidalgo County	Public
2017	Pine Hill Landfill	Census Tract 104, Gregg County	Private
2017	NTMWD 121 Regional Disposal Facility	Census Tract 302.01, Collin County	Public
2018	Atascocita RDF	Census Tract 2503.01, Harris County	Private
2018	Seabreeze Environmental Landfill	Census Tract 6641, Brazoria County	Private
2018	Blue Ridge LF	Census Tract 6707, Fort Bend County	Private
2019	Arlington LF	Census Tract 1131.02, Tarrant County	Public
2019	Galveston County LF	Census Tract 7233, Galveston County	Private
2020	Skyline LF	Census Tract 169.03, Dallas County	Private
2020	Coastal Plains RDF	Census Tract 7234, Galveston County	Private
2021	Tessman Road Landfill	Census Tract 1318.02, Bexar County	Private
2021	C.M. Hinton Jr Regional Landfill	Census Tract 181.24, Dallas County	Public
2022	Twin Oaks Landfill	Census Tract 1803.01, Grimes County	Public

Note: This table lists LFG project host landfills in Texas by year of first appearance (first treatment year), including their tract location and ownership type.

3.2 Nightlight Intensity

Nighttime light is measured using the VIIRS Day Night Band Annual V2 product, which provides annual radiance composites at 468.83 meter resolution (Elvidge et al., 2021). This measure is used as proxies for local economic activity, infrastructure growth, and industrial operations. We extract tract-level average radiance values for each year by overlaying the VIIRS raster data onto census tract boundaries. All radiance values are top-coded and cleaned following standard preprocessing procedures to remove ephemeral light sources and sensor noise. Figures 1a and 1b show nightlight intensity surrounding Atascocita Regional Disposal Facility in Harris County, separately for 2017 (Panel a) and 2023 (Panel b).



(a) Nightlight Intensity, 2017

(b) Nightlight Intensity, 2023

Figure 1: Changes in nightlight intensity surrounding Atascocita Regional Disposal Facility, 2017–2023. Warm colors indicate higher radiance and thus stronger nighttime illumination.

3.3 Landuse and Landcover

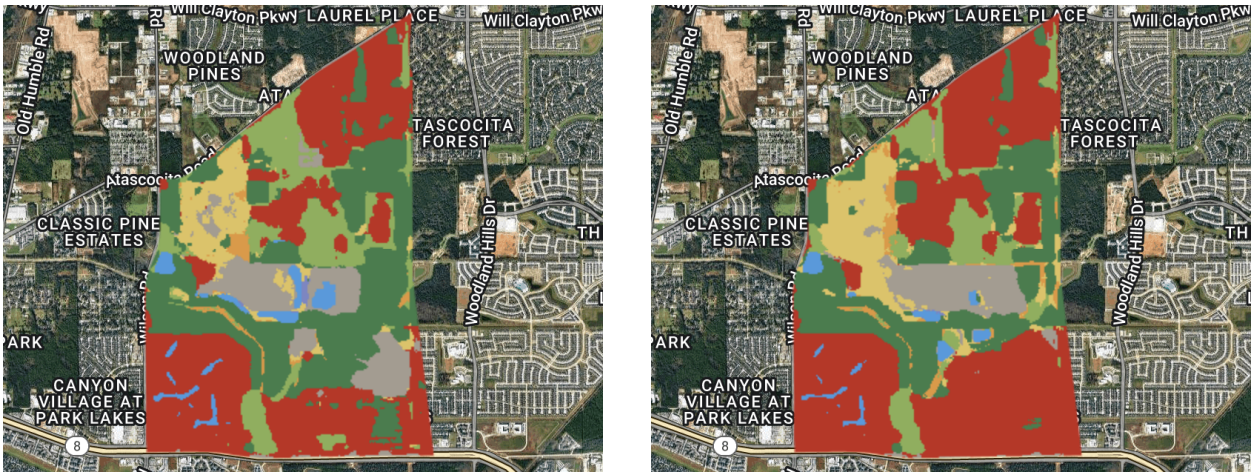
Land cover data is constructed from Dynamic World Data at 10-meter resolution (Brown et al., 2022). Continuous coverage for Texas begins in 2015, which sets the lower bound for the panel. We classify pixels into water, trees, grass, flooded vegetation, crops, shrub and scrub, bare ground, snow or ice, and built area. Built area includes roads, structures, and other hardened surfaces. For each tract year, we compute the share of land in each category. In the matched sample, land cover records are available for all 1,581 tracts across the 2015 to 2023 period, yielding 14,229 tract year observations. Figures 2a and 2b show the land cover classifications surrounding Atascocita

Regional Disposal Facility in Harris County for 2017 (Panel a) and 2023 (Panel b).

Table 2: Land Use and Land Cover (LULC) Classification

LULC Type	Description
Water	Permanent and seasonal water bodies
Trees	Includes primary and secondary forests, as well as large-scale plantations
Grass	Natural grasslands, livestock pastures, and parks
Flooded vegetation	Mangroves and other inundated ecosystems
Crops	Include row crops and paddy crops
Shrub & Scrub	Sparse to dense open vegetation consisting of shrubs
Built Area	Low- and high-density buildings, roads, and urban open space
Bare ground	Deserts and exposed rock
Snow & Ice	Permanent and seasonal snow cover

Note: This table summarizes the classification of Land Use and Land Cover (LULC) categories used in the analysis.



(a) Land Cover Classification, 2017

(b) Land Cover Classification, 2023

Figure 2: Changes in land cover composition surrounding Atascocita Regional Disposal Facility, 2017–2023. Classifications are derived from Dynamic World, where colors denote dominant land use types such as built-up areas, vegetation, and barren land. In 2017, substantial portions of the area consisted of vegetation and mixed land cover. By 2023, these vegetated areas were increasingly replaced by built-up areas, indicating growth in infrastructure.

3.4 Census Socioeconomic Data

Socioeconomic outcomes come from the U.S. Census Bureau's American Community Survey (ACS) 5 year estimates. We extract tract level measures of income, employment, racial composition, and population characteristics. The core variables include aggregate household income, aggregate individual income, number of employed individuals, total labor force, racial composition (White,

Black, Asian, Hispanic), number of households, and total population. We adjust all income measures to 2015 dollars using adjustment factors. Each tract is identified by its GEOID, along with state, county, and tract name, allowing integration with LMOP and geospatial datasets.

Table 3: American Community Survey (ACS) Variable Definitions

Variable	**Description**
Aggregate Household Income	Total household income aggregated at the tract level
Aggregate Individual Income	Total individual income aggregated at the tract level
Employed Population	Number of employed individuals
Labor Force Population	Total labor force
White Population	Number of individuals identifying as White (non-Hispanic)
Black Population	Number of individuals identifying as Black or African American
Asian Population	Number of individuals identifying as Asian
Hispanic Population	Number of individuals identifying as Hispanic or Latino (any race)
Number of Households	Total number of households in the tract
Total Population	Total tract population
Census Tract Name	Tract name (from ACS)
State	Two-letter state abbreviation
County	County name
Tract Code	Census tract code (within county)
Survey Year	ACS 5-year estimate reference year
GEOID	Full geographic identifier (state & county & tract)
Adjustment Factor	Inflation or normalization adjustment factor
Aggregate Household Income (Adjusted)	Inflation-adjusted aggregate household income
Aggregate Individual Income (Adjusted)	Inflation-adjusted aggregate individual income
Mean Household Income (2015 USD)	Mean household income adjusted to 2015 dollars
Mean Individual Income (2015 USD)	Mean individual income adjusted to 2015 dollars

Note: Variables are derived from the U.S. Census Bureau's American Community Survey (ACS) 5-year estimates at the census tract level. All income variables are adjusted to 2015 USD for comparability across years.

We construct an annual tract level panel by integrating the LMOP facility records, VIIRS nightlight data, land cover classifications, and ACS socioeconomic measures. First, each landfill site is geocoded and linked to the census tract in which it is located, and we assign treatment status based on the LMOP reported project initiation year. Second, we merge VIIRS radiance values and land cover shares by intersecting tract boundaries with satellite rasters for each year. Third, we append ACS socioeconomic variables using tract GEOIDs, ensuring consistent boundaries over time. Because land cover data and ACS indicators are available from 2015 onward, and LMOP facilities are observed through 2023, the final dataset spans nine years (2015-2023). The resulting panel includes 5,089 census tracts within three miles of any landfill in Texas, of which 1,020 tracts are located near the 16 operational LFG facilities. After propensity score matching on pre treatment characteristics, our analysis sample consists of 1,581 tracts (887 treated, 694 unique

controls) observed over the nine year period, yielding 14,229 tract year observations. This unified panel structure enables us to compare treated and comparable untreated tracts over a consistent period using matched and staggered difference in differences designs.

Table 4: Summary of Data Sources

Category	Source	Years	Spatial Unit
Satellite Imagery	Sentinel-2 (10m) (Nightlight, Landcover)	2015–2024	10m x 10m
Census Data	ACS 5-year estimates (income, population)	2013–2023	tract-level
LFG Project Data	EPA LMOP database	2013–2023	Facility coordinates

4 Methods

4.1 Propensity Score Matching

The first step in our empirical strategy is to construct a comparison group of census tracts that resemble treated tracts in their pre treatment characteristics. Because LFG facilities are not randomly assigned across locations, tracts hosting these projects differ systematically from non-host tracts in pre treatment characteristics. Our matching approach addresses this selection problem by constructing a comparison group of untreated tracts that share similar observable characteristics with treated tracts in the year prior to treatment.

We estimate propensity scores where the dependent variable equals one for tracts that eventually receive an LFG facility and zero otherwise. The model includes seven pre treatment covariates measured in the year immediately preceding project initiation: log mean income, nightlight intensity, built up area share, tree cover share, white population share, black population share, and employment rate. We include nightlight intensity and land cover share as matching covariates because these satellite derived measures capture pre existing spatial development patterns that strongly predict facility placement. Landfills with sufficient infrastructure and economic activity are more likely to attract LFG projects, making these characteristics critical confounders. For treated tracts, we use observations from t-1 where t is the first treatment year. For never treated tracts, we use 2015 values to maintain temporal consistency.

After matching, all standardized differences fall below 0.06. The matched sample retains 887 treated tracts and 694 unique controls, yielding an effective control sample size of 539. We then

rebuild the full annual panel for all matched tracts from 2015 to 2023, resulting in 1,581 tracts and 14,229 tract year observations. This matched panel limits extrapolation and ensures that treatment and comparison tracts have similar baseline socioeconomic and land cover profiles.

Table 5: Descriptive Statistics Before Matching

Outcome	Control (N = 4,199)	Treated (N = 890)	p-value
Nightlight Intensity	23.5 ± 24.5	26.8 ± 19.4	0.000
Mean Income (2015 USD)	10.1 ± 0.5	10.1 ± 0.5	0.008
Built-up Area Share	0.6 ± 0.4	0.7 ± 0.3	0.000
Tree Cover Share	0.2 ± 0.2	0.1 ± 0.2	0.000
White Population Share	0.8 ± 0.2	0.7 ± 0.2	0.000
Black Population Share	0.1 ± 0.2	0.2 ± 0.2	0.000
Employment Rate	0.9 ± 0.1	0.9 ± 0.0	0.000

4.2 Staggered Difference-in-Differences

To estimate the causal effects of LFG projects, we use a staggered difference-in-differences design that use variation in the timing of project initiation across census tracts. Let G_i denote the first year in which tract i is treated. Treatment cohorts begin between 2015 and 2023, with the largest cohorts in 2018 and 2019.

Our primary estimates use the estimator of Callaway and Sant'Anna (2021), which identifies cohort- and time-specific effects by comparing each treated cohort to tracts that are not yet treated in the same calendar year. The estimand is the group-time average treatment effect:

$$ATT(g,t) \equiv \mathbb{E}\left[Y_{it}(1) - Y_{it}(0) \,\middle|\, G_i = g\right], \quad t \geq g, \tag{1}$$

where $Y_{it}(1)$ and $Y_{it}(0)$ denote potential outcomes with and without treatment, respectively.

Identification relies on a conditional parallel trends assumption. Absent treatment, changes in outcomes for cohort g would have followed the same trends as those for tracts not yet treated at time t, conditional on pre-treatment covariates X_i:

$$\mathbb{E}\left[Y_{it}(0) - Y_{i,t-1}(0) \,\middle|\, G_i = g, X_i\right] = \mathbb{E}[Y_{it}(0) - Y_{i,t-1}(0) \mid G_i > t, X_i], \quad \forall t < g. \tag{2}$$

We summarize treatment dynamics by indexing effects by event time $k = t - g$ and aggregating

the group-time effects across cohorts. As a robustness check and point of comparison with analysis, we also estimate a conventional two-way fixed effects model with tract and year fixed effects. Because TWFE event-study coefficients can be biased under staggered adoption with heterogeneous treatment effects, we interpret these results as a benchmark rather than our primary estimates.

5 Results

5.1 How different are treated and untreated tracts?

We begin by examining differences between tracts that host LFG facilities and those that do not. Table 6 presents descriptive statistics for key covariates in the pre treatment period, comparing the 890 treated tracts to 4,199 potential control tracts. Treated tracts exhibit significantly higher levels of economic activity and development. Average nightlight intensity is 14 percent higher (26.8 vs. 23.5, $p < 0.001$), built up area share is substantially larger (0.68 vs. 0.55, $p < 0.001$), and tree cover is correspondingly lower (0.14 vs. 0.18, $p < 0.001$). The demographic composition also differs systematically, with the white population share 11 percentage points lower in treated tracts (0.66 vs. 0.77, $p < 0.001$) and the black population share 7 percentage points higher (0.18 vs. 0.11, $p < 0.001$). Employment rates are modestly higher in treated areas (0.94 vs. 0.92, $p < 0.001$), though mean income levels are nearly identical. These pre-treatment differences underscore the non random placement of LFG facilities and motivate our matching strategy as shown in Figure 4.

Figure 3 show that our propensity score matching successfully addresses these imbalances. Before matching, six of seven covariates exhibit standardized differences exceeding 0.1, with the largest imbalances in white population share (-0.54) and built up area (0.44). After implementing nearest neighbor matching with a 0.1 caliper, all standardized differences fall below 0.06, which is well within the conventional thresholds for adequate balance. Figure 4 illustrates this improvement through propensity score distributions, showing substantial convergence between the treated and control groups across all dimensions. These diagnostics provide confidence that our matched sample isolates tracts with similar pre treatment characteristics, addressing the selection bias inherent in facility placement.

Table 6: Covariate Balance Before and After Matching

Variable	Treated Mean	Control Mean	SMD
Before Matching			
Log Income	10.1247	10.0786	0.0998
Nightlight Inte nsity	26.7931	23.5272	0.1684
Built-up Area Share	0.6796	0.5508	0.4385
Tree Cover Share	0.1419	0.1781	-0.2278
White Population Share	0.6562	0.7705	-0.5407
Black Population Share	0.1838	0.1079	0.3830
Employment Rate	0.9371	0.9212	0.3488
After Matching			
Log Income	10.1252	10.1445	-0.0417
Nightlight Intensity	26.7682	27.7564	-0.0510
Built-up Area Share	0.6792	0.6964	-0.0585
Tree Cover Share	0.1419	0.1359	0.0377
White Population Share	0.6580	0.6594	-0.0069
Black Population Share	0.1820	0.1737	0.0416
Employment Rate	0.9369	0.9369	0.0002

Note: SMD = Standardized Mean Difference. Absolute values < 0.10 indicate acceptable balance.

5.2 Does LFG have an effect?

We estimate treatment effects using two approaches: the staggered differences-in-differences, and a conventional two-way fixed effects model. Table 7 reports average treatment effects across the six outcomes considered.

Table 7: Overall ATT Estimates (Callaway–Sant'Anna)

Outcome	ATT	SE	CI_{lo}	CI_{hi}
Nightlight Intensity	0.1562	0.3880	-0.6030	0.9160
Mean Income (2015 USD)	-686.1411	432.0000	-1533.000	161.000
Built-up Area Share	0.0078***	0.00155	0.00474	0.01080
Tree Cover Share	-0.0081***	0.00130	-0.01070	-0.00561
Black Population Share	-0.0032	0.00344	-0.00998	0.00351
Employment Rate	-0.0015	0.00181	-0.00505	0.00204

Note: Standard errors are clustered at the census tract level. * p<0.10, ** p<0.05, *** p<0.01.

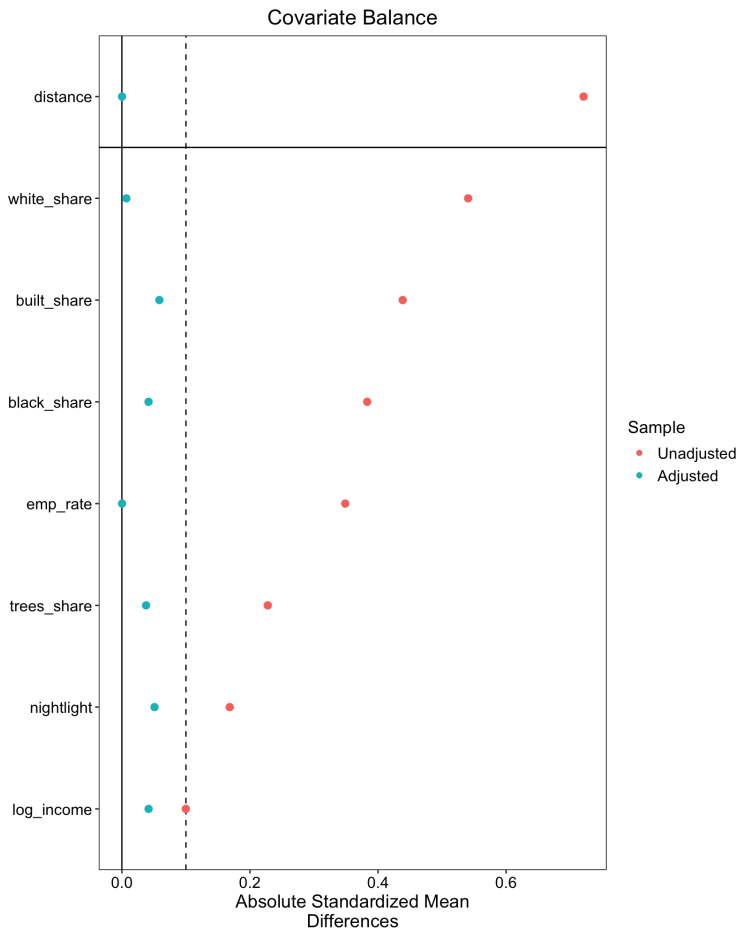


Figure 3: Absolute standardized mean differences for covariates before matching and after matching. Red points represent the unmatched sample and blue points represent the matched sample. The vertical dashed line marks the conventional balance threshold.

Spatial Development Effects

Across all methods, we obtain small positive coefficients for the built-up area following project initiation. Estimates range from 0.0043 in the two-way fixed effects model to 0.0078 in the staggered estimator. These magnitudes correspond to an increase of roughly one to two percent relative to the pre-treatment mean. The sign and scale of the estimates are stable across methods, which suggests that they do not arise from a specific modeling choice.

Despite this apparent consistency, the event study diagnostics make clear that the identifying assumptions are not fully met for this outcome. Four of the five pre-treatment coefficients for built-up area are statistically significant, and the largest of these is similar in magnitude to the post-treatment estimates. Tree cover shows even stronger pre-treatment movement, with all five



Figure 4: Propensity score distributions for treated and control tracts before and after matching. Matching substantially improves overlap between groups, reducing imbalance in the probability of treatment assignment.

pre-treatment coefficients significant. Nightlight intensity also shows meaningful pre-treatment variation. These patterns indicate that treated and untreated tracts were on different trajectories before facility operation, even after matching on levels. They therefore limit the credibility of any causal interpretation for these spatial indicators.

The TWFE model produces the smaller built area estimate. This is consistent with the idea that once time-varying unobserved trends are allowed to differ across units, the magnitude of any post-treatment change becomes modest. We interpret this that built-up area continues to rise in treated locations relative to matched controls, but part or possibly all of this difference reflects continuation of pre-existing trends rather than a change induced by LFG projects.

Economic and Demographic Outcomes

Income, employment, and demographic composition show far cleaner pre-treatment patterns. The event study figures for these variables have pre-treatment coefficients that are close from zero, which supports the identification strategy for these outcomes.

For income, estimates from all methods fluctuate around zero with no consistent pattern and no statistical significance. The implied effects are small relative to tract-level variation and are not robust across methods. The employment rate shows a similar pattern. Pre-treatment coefficients are flat and insignificant. Post-treatment estimates in the staggered estimator remain close to zero. TWFE model produce small positive coefficients, but these are neither large nor stable enough to be interpreted as meaningful evidence of an employment effect. Racial composition shows no detectable change. Both pre-treatment and post-treatment coefficients for the Black population share are close to zero with narrow confidence intervals. The same holds for the other population shares. Confidence intervals rule out even moderate changes in composition.

The results indicate the absence of measurable economic or demographic effects from LFG facilities at the tract scale within the available time frame. The data support the presence of differential physical development trends near treated sites, but these trends begin before facility operation and therefore cannot be cleanly attributed to treatment.

Table 8: Treatment Effects on Local Economic and Spatial Outcomes

	Estimation Method	
Outcome	DID	TWFE
Panel A: Economic Outcomes		
Mean Income (2015 USD)	-686.14	-26.40
	(443.00)	(185.06)
Employment Rate	-0.0015	0.0056***
	(0.0020)	(0.0012)
Panel B: Spatial Outcomes		
Nightlight Intensity	0.1562	0.2605
	(0.3910)	(0.1730)
Built-up Area Share	0.0078***	0.0043***
	(0.0017)	(0.0013)
Tree Cover Share	-0.0081***	-0.0075***
	(0.0014)	(0.0012)
Panel C: Demographic Outcomes		
Black Population Share	-0.0032	0.0002
	(0.0032)	(0.0019)
Observations	7,983	14,229
Census Tracts	1,581	1,581

Notes: Standard errors in parentheses, clustered at tract level. DID uses Callaway and Sant'Anna (2021) with doubly robust estimation. TWFE includes tract and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Pre-trend Assessment

The event study estimates provide mixed evidence on the parallel trends assumption. Three outcomes satisfy the identifying assumption, while built-up area does not. Black population shows all five pre-treatment coefficients centered near zero with narrow confidence intervals. Post-treatment estimates remain flat and statistically insignificant, indicating no detectable demographic change. Employment rate also satisfies parallel trends. Pre-treatment coefficients are small and indistinguishable from zero, and post-treatment estimates remain imprecise with confidence intervals spanning zero throughout the post-period. Mean income displays a similarly clean pre-treatment pattern, with all coefficients close to zero and statistically insignificant. Post-treatment point estimates fluctuate, but the confidence intervals are wide, and the effects are neither statistically significant.

We observe a meaningful increase in built-up, although the pre-trend shows a sign of increase two years prior to the event. The pre-treatment trend suggests treated tracts were already experiencing differential spatial development before LFG facilities became operational. While the final post-treatment estimate shows a large coefficient of approximately 0.055, this likely reflects continuation or acceleration of pre-existing trends rather than a treatment-induced change. Even after propensity score matching on pre-treatment levels, treated and control tracts followed different trajectories.

In summary, our results provide limited evidence that LFG facilities generate the local economic benefits anticipated by environmental justice advocates and policymakers. The clearest effect is a small increase in built-up area, suggesting modest infrastructure or commercial development in surrounding tracts. However, we find no evidence of income gains, employment growth, or demographic changes. These null findings persist across multiple estimation approaches and are robust to alternative specifications, suggesting that any economic benefits from LFG operations, if they exist, are too small to detect with our data or accrue outside the geographic or temporal scope of our analysis.

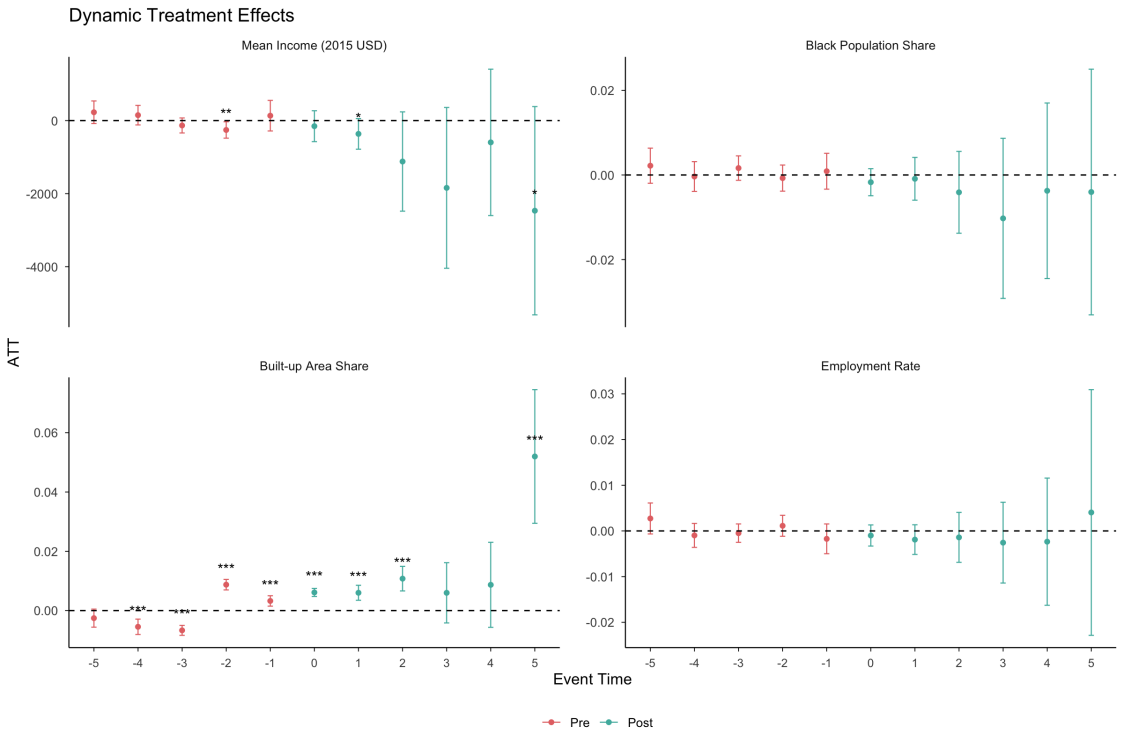


Figure 5: Dynamic treatment effects for nightlight intensity, built up area share, employment rate, and mean income estimated using the staggered difference in differences method of Callaway and SantAnna, plotted relative to the first treatment year.

6 Discussion and Conclusion

This study examines whether LFG projects produce local economic gains for nearby communities. Using matched census tracts in Texas and staggered treatment timing, we combine survey based socioeconomic measures with satellite based indicators of land use and night activity. We ask whether the environmental justification for these facilities is accompanied by measurable economic benefits for host communities.

The results do not support the common claim that LFG projects generate meaningful economic improvements at the local level. For income, employment, and demographic composition the identifying assumptions appear reasonable, but the estimated effects remain close to zero across all methods. These findings suggest that whatever economic activity is associated with construction or operation of these projects does not translate into tract level changes in income or employment within the time horizon observed.

The only consistent positive estimate appears for built up areas, yet its interpretation is limited

by clear violations of parallel trends. Treated tracts were already on a steeper development path before facility operation. This pattern persists across multiple specifications and is visible in every pre-treatment period. Once these differential trends are taken seriously, the remaining evidence points to at most a modest continuation of pre-existing development rather than a change induced by LFG activity.

These findings carry two implications for research on environmental infrastructure. First, physical improvements near a site cannot be assumed to represent economic spillovers caused by the installation itself. Many landfills are located in areas already undergoing low intensity commercial growth such as warehousing or industrial uses. If such growth predates treatment, attributing it to LFG projects is not credible. Second, the scale of these facilities is small. Most employ few permanent workers and supply energy to markets that are not spatially concentrated around the landfill. For these reasons tract level economic indicators are unlikely to move even if the facility has some operational demands. Several limitations define the scope of the conclusions. First, differential pre-treatment trajectories limit what can be said about spatial outcomes. Second, ACS five year estimates smooth short run changes and will attenuate the measured impact of any event that takes place within a narrow time range. Third, the tract radius may not match the true spatial extent of any benefits. Effects that occur at the parcel scale or emerge in county budgets will not be captured in this design. Fourth, sample size and treatment variation are limited. Estimating heterogeneity by technology type, ownership model, or local policy context requires more facilities than Texas provides.

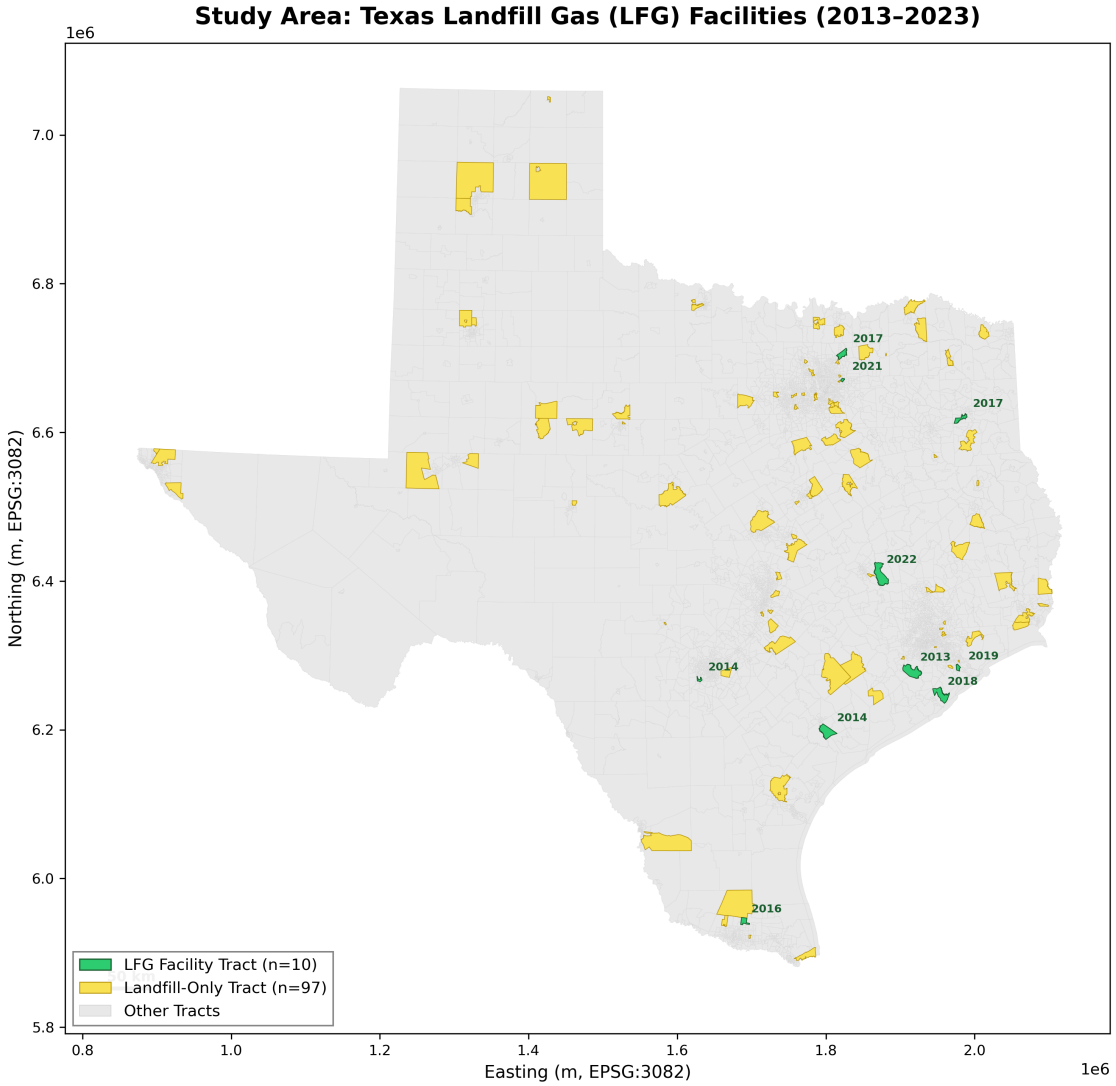
LFG facilities produce environmental gains through methane capture but do not generate detectable economic gains for nearby communities in the medium run. Claims that such projects serve as engines of local economic development are not supported by the available evidence. If policymakers intend to deliver economic benefits to host communities, they will need instruments other than the installations themselves. Direct local hiring policies, community benefit agreements, or targeted investment programs are likely required if the distribution of gains is a central objective.

Conclusion

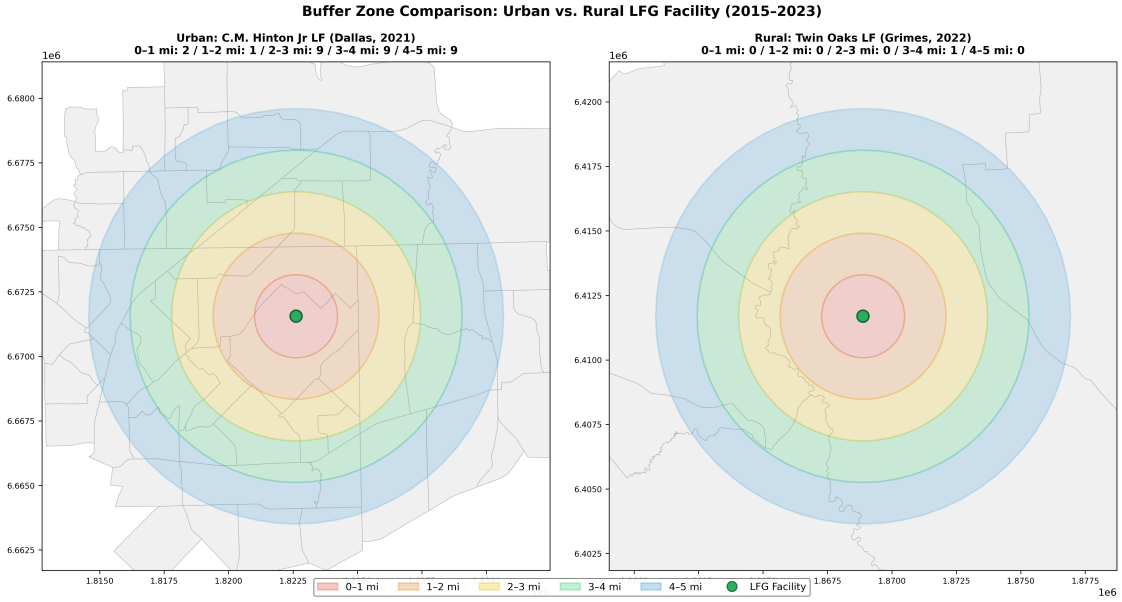
Despite these limitations, our results carry important implications for environmental policy and environmental justice advocacy. The absence of detectable income or employment gains suggests that the economic benefits of LFG facilities may be overstated in policy debates and facility siting decisions. While these projects serve legitimate environmental objectives by capturing methane emissions and generating renewable energy, policymakers should not assume that environmental infrastructure automatically delivers economic co-benefits to host communities. If distributional equity is a policy objective, additional mechanisms, such as local hiring requirements, community benefit agreements, or targeted investments in surrounding neighborhoods, may be necessary to ensure that communities bearing the proximity costs of waste infrastructure also share in any economic gains.

More broadly, our findings highlight the importance of empirically validating claims about win-win environmental policies that promise both ecological and economic benefits. The intuition that green infrastructure projects will stimulate local economic development is appealing, but it requires empirical verification, particularly in environmental justice contexts where host communities often lack the political and economic resources to negotiate favorable terms. Our null results for income and employment, combined with the modest spatial development effect, suggest that the reality of LFG projects falls short of their economic promise. Future research should investigate whether this pattern extends to other forms of environmental infrastructure, examine longer-run outcomes as additional data become available, and explore policy designs that could better align environmental and economic objectives in facility siting decisions.

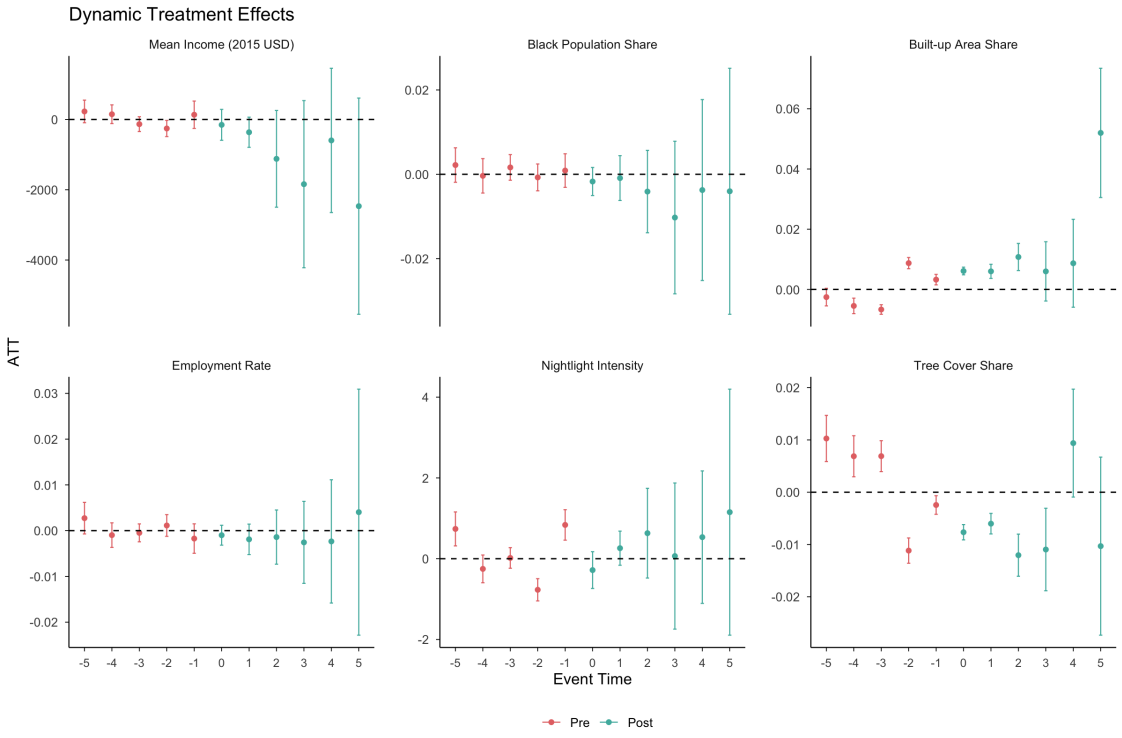
Appendix



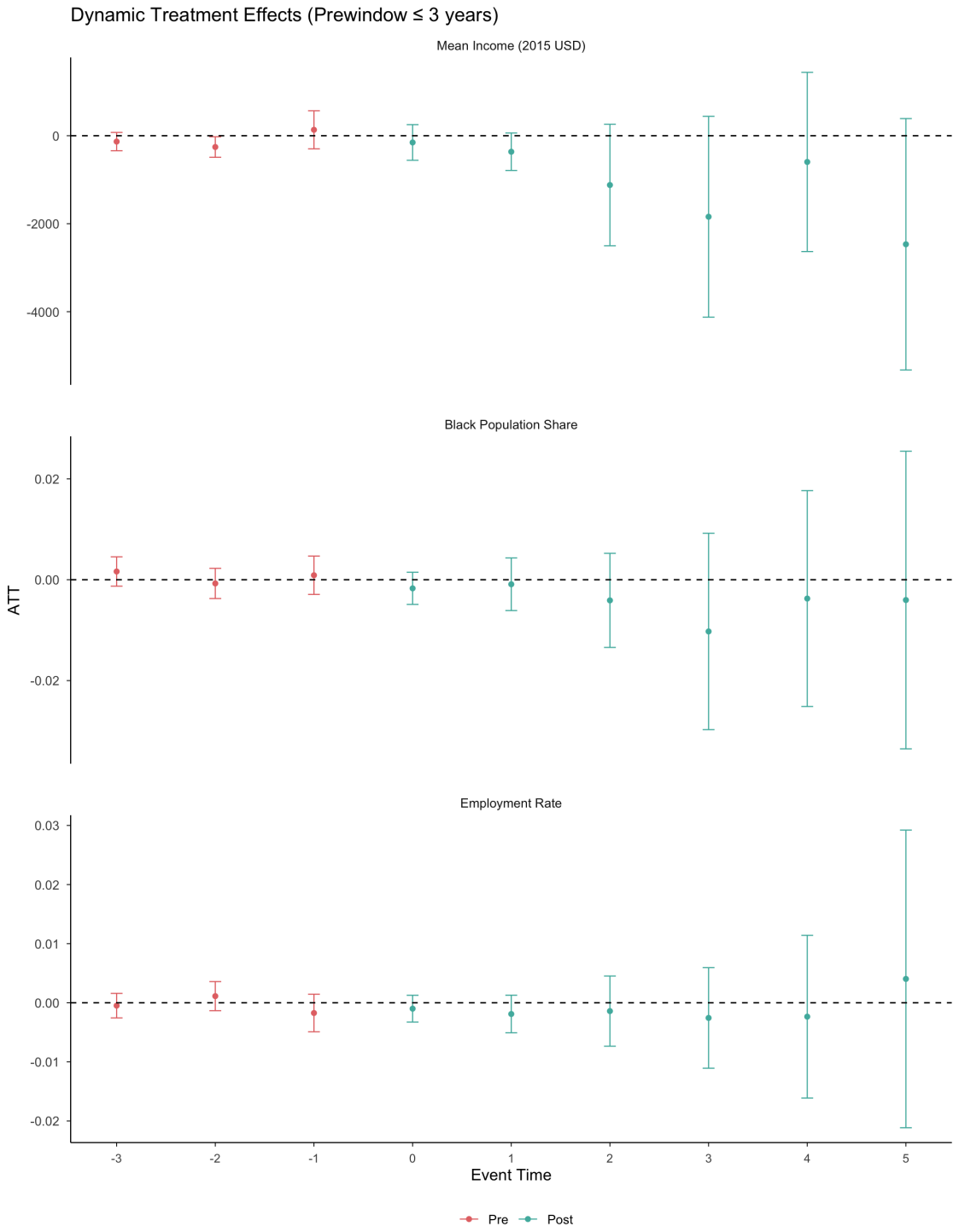
Appendix 1: Study Area Map



Appendix 2: 0–5 Miles Buffer from LFG Tract



Appendix 3: Event study estimates for nightlight intensity, mean income, built-up area share, tree cover share, black population share, and employment rate, showing pretreatment parallel trends and small post-treatment effects with confidence intervals for all event time coefficients.



Appendix 4: Dynamic treatment effects for mean income, black population share, and employment rate estimated using the staggered difference-in-differences method of Callaway and Sant'Anna, based on a 3-year pre-window.

Robustness Check (2015–2024)

Table 9: Robustness: Average Treatment Effects — Cumulative Buffer (2015–2024)

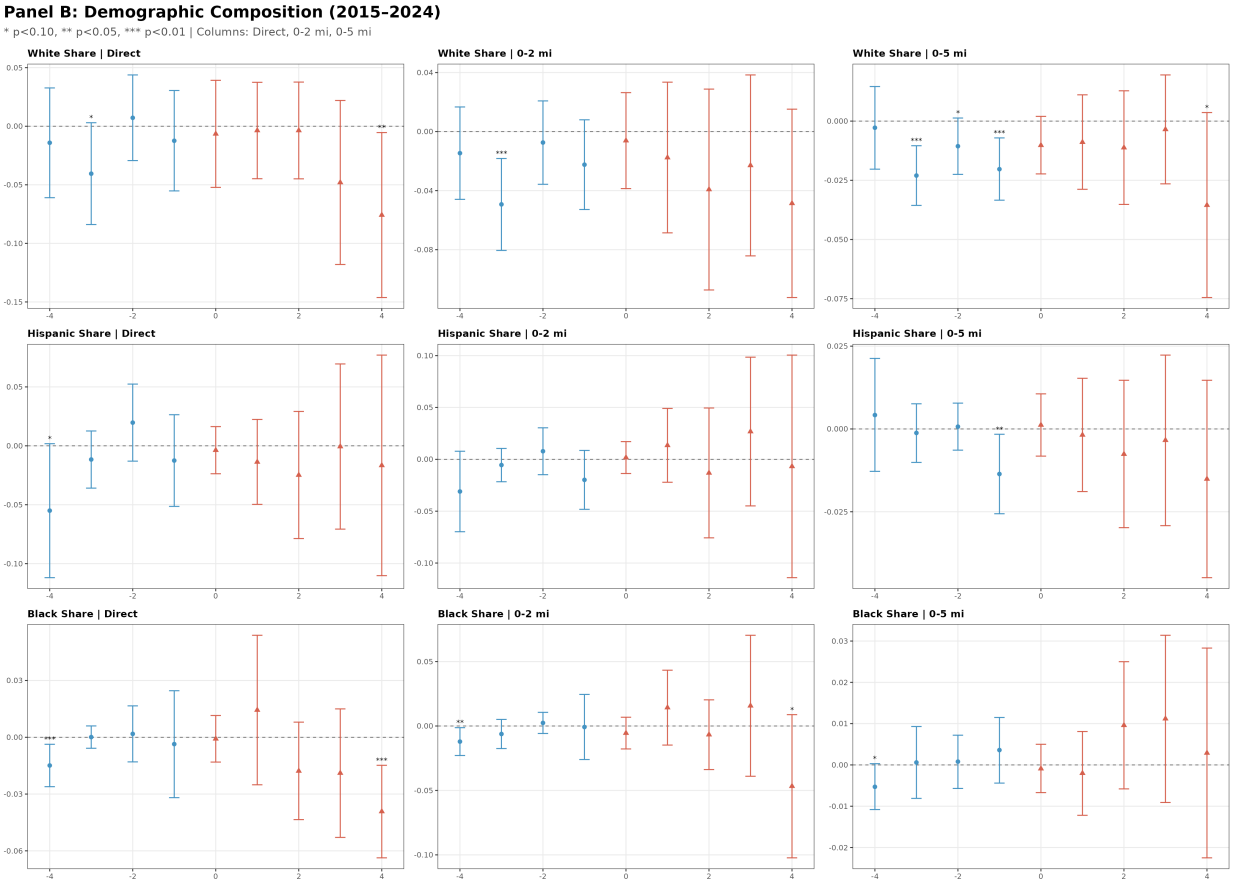
	Direct	0–2 mi	0–5 mi
A. Economic Outcomes			
Log real per capita income	0.003	0.002	−0.004
	(0.056)	(0.040)	(0.020)
Log real mean household income	0.002	0.015	−0.001
	(0.056)	(0.044)	(0.018)
Unemployment rate	0.006	−0.003	−0.003
	(0.011)	(0.009)	(0.004)
Real median rent ($)	30.00	2.62	29.25
	(70.77)	(58.96)	(29.43)
B. Demographic Composition			
Hispanic share	−0.009	0.004	−0.004
	(0.023)	(0.021)	(0.007)
White share	−0.049***	−0.036**	−0.028***
	(0.017)	(0.016)	(0.011)
Black share	−0.009	−0.006	0.007
	(0.011)	(0.010)	(0.006)
C. Satellite Variables			
Nightlight intensity	0.06	−0.15	−0.30*
	(0.32)	(0.36)	(0.18)
Built-up share	0.017*	0.017*	0.004
	(0.010)	(0.010)	(0.006)
Tree cover share	−0.019	−0.011	−0.003
	(0.023)	(0.013)	(0.004)
Treated tracts	19	30	169
Control tracts	77	166	762
Panel	B (2015–2024)		
Estimator	Doubly Robust DiD		

Notes: ATT with clustered standard errors (census tract) in parentheses. Doubly robust DiD with staggered adoption (Callaway and Sant'Anna, 2021), applied to the PSM-matched sample. Unit and year fixed effects included. Cumulative buffers. Monetary values in 2023 dollars (C-CPI-U). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

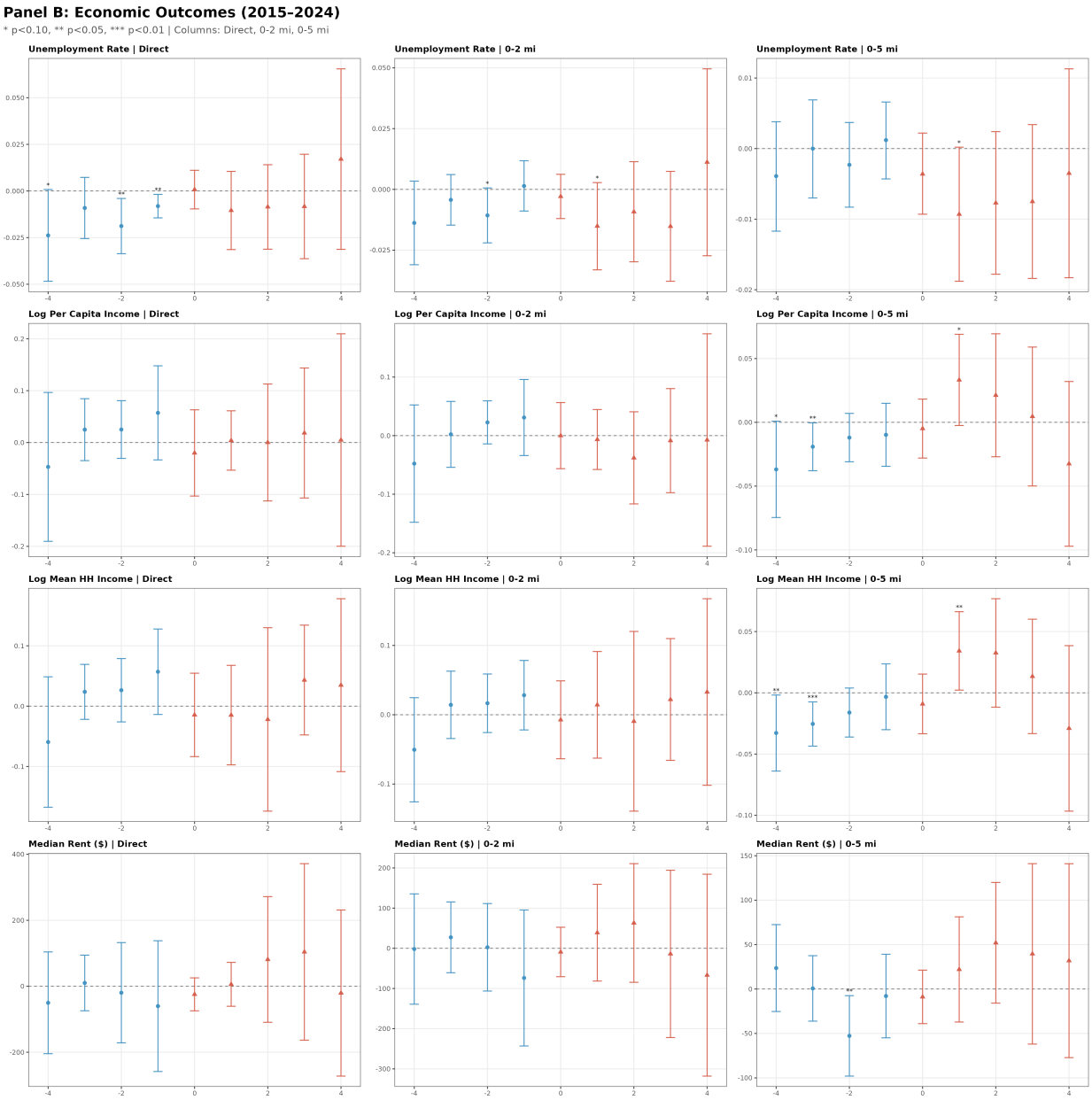
Table 10: Robustness: Fixed Effects Counterfactual Estimator (2015–2024)

	Direct	0–2 mi	0–5 mi
A. Economic Outcomes			
Log real per capita income	—	—	—
Unemployment rate	−0.027***	−0.019***	−0.011***
	(0.006)	(0.007)	(0.004)
Real median rent ($)	−158.37	−82.29	45.24
	(204.73)	(158.04)	(63.56)
Log real mean household income	−0.058**	−0.005	−0.009
	(0.029)	(0.029)	(0.015)
B. Demographic Composition			
Hispanic share	−0.028**	−0.025**	−0.015
	(0.011)	(0.013)	(0.011)
White share	0.050	0.024	−0.013
	(0.060)	(0.042)	(0.026)
Black share	0.019	0.014	0.008
	(0.021)	(0.017)	(0.007)
C. Satellite Variables			
Nightlight intensity	−0.19	−0.65	−1.44***
	(0.43)	(0.58)	(0.31)
Built-up share	0.004	0.022*	0.003
	(0.010)	(0.013)	(0.005)
Tree cover share	0.012	0.018**	0.007***
	(0.007)	(0.007)	(0.002)
Treated tracts	19	30	169
Control tracts	77	166	762
Panel	B (2015–2024)		
Estimator	fect (IFE method)		

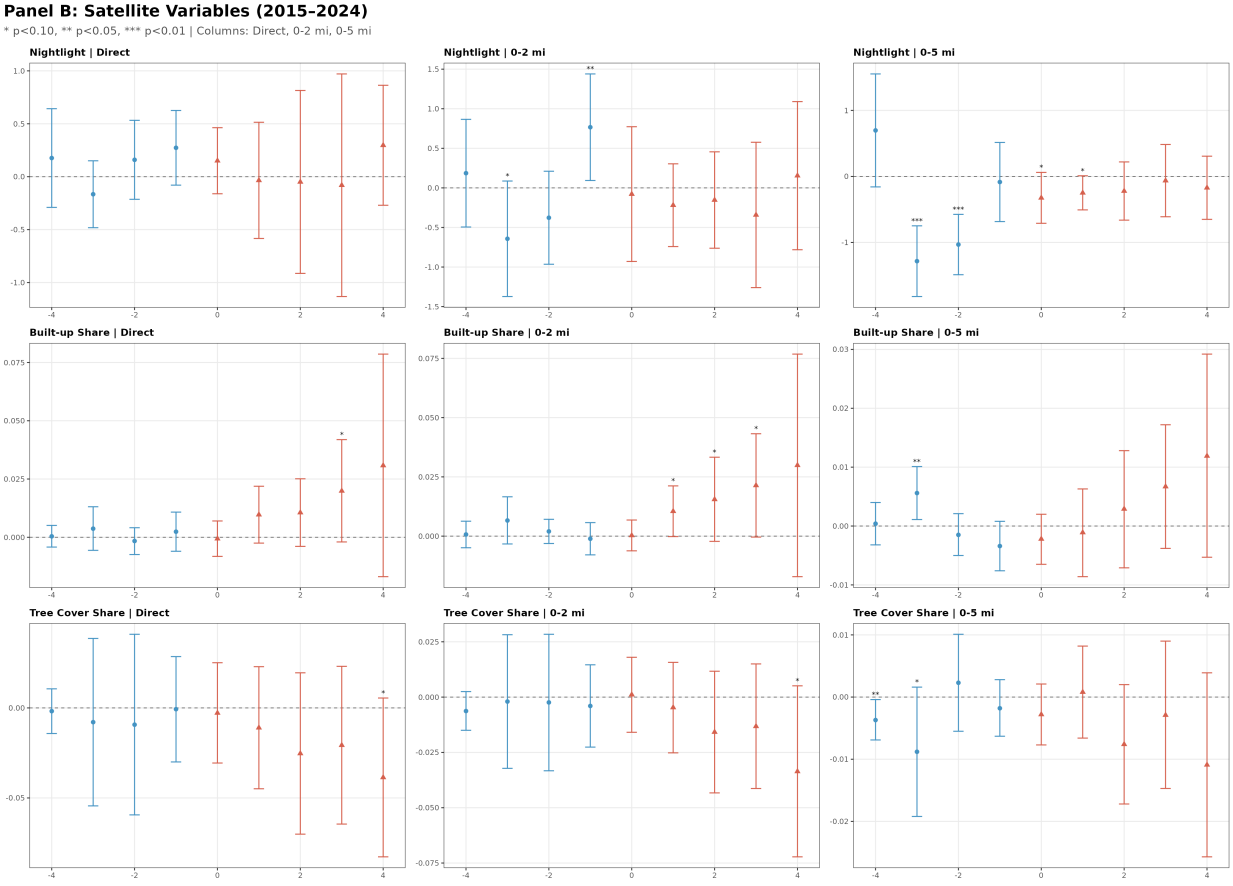
Notes: ATT with bootstrap standard errors in parentheses. Fixed effects counterfactual estimator using the interactive fixed effects (IFE) method (Liu et al., 2024), applied to the PSM-matched sample. Cumulative buffers. Monetary values in 2023 dollars (C-CPI-U). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



Appendix 5: Demographic Outcomes



Appendix 6: Economic Outcomes



Appendix 7: Satellite-Derived Outcomes

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