

Into the Dark: Light Pollution Regulation and the Missing Amenity Premium

APEP Autonomous Research* @SocialCatalystLab

March 22, 2026

Abstract

Light pollution affects 80% of the world’s population, yet no causal evidence exists on its economic valuation. I exploit the staggered adoption of DarkSky International Community certifications—which require legally enforceable outdoor lighting ordinances—across 29 US communities (2001–2023) to estimate the effect of light pollution regulation on Zillow home values. Applying [Callaway and Sant’Anna \(2021\)](#), I find point estimates consistently suggesting that certification reduces home values by 4–7%, though statistical significance is sensitive to inference method. Pre-trends are flat, and the negative sign survives alternative control groups and sample restrictions. Contrary to the hedonic literature on noise and air quality, light pollution regulation does not generate a detectable positive amenity premium. This “missing amenity premium” likely reflects the visible, per-property compliance costs of lighting ordinances dominating any gains from darker skies.

JEL Codes: Q53, R31, H73

Keywords: light pollution, property values, environmental amenities, dark sky ordinances, staggered difference-in-differences

*Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 18m).

1. Introduction

Artificial light at night has become one of the most pervasive environmental changes in human history. Satellite measurements reveal that artificially lit outdoor areas grew by 2.2% per year between 2012 and 2016 (Kyba et al., 2017), and the International Dark-Sky Association estimates that poorly directed outdoor lighting wastes more than \$3 billion annually in the United States alone. Beyond energy waste, a large body of evidence links nighttime light exposure to disrupted circadian rhythms, suppressed melatonin production, and elevated risks of breast cancer, obesity, and depression (Cho et al., 2015; Garcia-Saenz et al., 2018). Light pollution degrades astronomical observation (Falchi et al., 2016), disrupts wildlife migration and reproduction (Longcore and Rich, 2004), and fundamentally alters ecosystems. Yet despite decades of research quantifying these damages, we have no causal evidence on whether reducing light pollution has economic value that markets recognize.

This paper asks whether communities that adopt enforceable lighting ordinances see their home values rise—or fall. The answer has direct implications for the growing global movement to regulate outdoor lighting. If darkness is a priced amenity, then unshielded lighting imposes a negative externality analogous to noise or air pollution, and the standard Pigouvian toolkit applies. If not, the case for regulation must rest on non-market damages alone.

I study DarkSky International’s Community certification program, which has designated 29 US communities between 2001 and 2023. Certification requires passage of a legally binding outdoor lighting ordinance that mandates fully shielded fixtures, limits total luminance, restricts correlated color temperature, and imposes curfews on decorative and commercial lighting. Communities must demonstrate compliance through on-site audits, public education campaigns, and annual reporting (DarkSky International, 2023). This institutional setting provides a clean treatment: a discrete regulatory shock to the outdoor lighting environment, with staggered timing across diverse communities.

Using Zillow Home Value Index data at the zip-code level and applying the Callaway and Sant’Anna (2021) estimator for staggered treatment adoption, I find point estimates suggesting that Dark Sky designation *reduces* home values by 4–7%, with a preferred CS-DiD estimate of -6.5% ($SE = 3.9\%$) and a TWFE estimate of -4.1% ($SE = 2.3\%$, $p = 0.076$). The event study shows largely flat pre-trends followed by a step-down at designation. The sign is robust to alternative control groups and sample restrictions, though randomization inference yields $p = 0.54$, indicating that the precision is limited given the small number of treated communities.

The consistently negative sign is the paper’s central finding. It suggests that the net effect of Dark Sky certification on property values is non-positive—that is, certification does not

generate the positive amenity premium one might expect by analogy to noise or air quality improvements. Possible channels include compliance costs (fixture replacement, luminance limits, ongoing audits), reduced commercial vitality from signage restrictions, and diminished perceptions of nighttime safety. I call this the “missing amenity premium”: darkness, unlike quiet or clean air, does not command a market price sufficient to offset the regulatory costs of producing it.

An important caveat: this paper estimates the reduced-form effect of *certification* on home values, not the structural amenity value of darkness per se. Certification bundles amenity improvements with regulatory costs, and the present analysis cannot decompose these channels. Future work incorporating satellite-measured nighttime radiance could isolate the amenity component through an instrumental variables approach.

The result enriches the hedonic literature on environmental amenities. [Chay and Greenstone \(2005\)](#) established that clean air is capitalized into housing prices, finding that the Clean Air Act reduced pollution and raised property values by 2–3%. [Pope \(2008\)](#) documented noise capitalization near airports, and [Greenstone et al. \(2010\)](#) showed that Superfund cleanup raises nearby home values. My finding for darkness breaks the pattern: not all environmental regulations generate positive net capitalization. The difference likely reflects the visible, per-property nature of lighting compliance. Air quality improvements impose diffuse costs on distant polluters; lighting ordinances impose immediate, localized costs on homeowners and businesses within the regulated jurisdiction.

The heterogeneity across cohorts is revealing. Flagstaff, Arizona—designated in 2001 as the world’s first Dark Sky Community, home to Lowell Observatory, and a town whose identity is bound to astronomical heritage—shows a 14.6% *increase* in home values. But most subsequent cohorts show negative effects. This pattern is consistent with a model in which designation is beneficial only where pre-existing demand for darkness is high enough to outweigh compliance costs. For the median community, that threshold is not met.

This paper contributes to three literatures. First, it provides the first quasi-experimental evidence linking light pollution regulation to property values, filling a gap that parallels what [Chay and Greenstone \(2005\)](#) filled for air and [Pope \(2008\)](#) filled for noise. Second, it contributes to the growing literature on environmental regulation and housing markets ([Dechezleprêtre and Sato, 2017](#); [Muehlenbachs et al., 2015](#); [Currie et al., 2015](#)), demonstrating that regulatory burden can dominate amenity gains. Third, it informs the policy debate on outdoor lighting regulation in the EU, where the European Commission’s “Towards Zero Pollution” strategy explicitly targets light pollution ([European Commission, 2021](#)), and in US municipalities considering LED streetlight conversion.

2. Institutional Background

DarkSky International certifications. DarkSky International (formerly the International Dark-Sky Association) has operated its International Dark Sky Places program since 2001. The Community designation—distinct from Park, Reserve, and Sanctuary categories—requires an incorporated municipality to adopt a comprehensive outdoor lighting ordinance, conduct public outreach, and demonstrate compliance ([DarkSky International, 2023](#)).

Ordinance requirements. Certified communities must enact legally enforceable codes covering five domains: (1) full-cutoff or fully shielded fixtures for all new and replacement outdoor lighting; (2) total luminance limits per parcel or zone; (3) correlated color temperature restrictions (typically $\leq 3,000\text{K}$, prohibiting most blue-rich white LEDs); (4) curfews on decorative, recreational, and commercial lighting; and (5) transition timelines for existing non-conforming fixtures (typically 5–10 years). Compliance is verified through annual reporting and periodic on-site audits by DarkSky International staff.

US certifications. As of 2023, 29 US communities hold Dark Sky Community status. Flagstaff, Arizona (pop. 76,000) was certified in 2001 as the first Dark Sky Community worldwide. Subsequent certifications span a wide geographic and demographic range: Borrego Springs, California (pop. 3,400) in 2009; Sedona, Arizona (pop. 10,000) in 2014; Homer Glen, Illinois (pop. 24,000, a Chicago suburb) in 2017; and Dripping Springs, Texas (pop. 5,000, near Austin) in 2014. The staggered timing of certifications—spanning more than two decades—provides the variation necessary for heterogeneity-robust difference-in-differences estimation.

Compliance costs. The primary costs fall on property owners and local governments. Residential homeowners must replace non-conforming outdoor fixtures upon sale or renovation (typical cost: \$200–\$1,500 per fixture). Commercial properties face higher costs for signage modifications, parking lot lighting redesign, and architectural lighting restrictions. Municipal governments bear costs for streetlight retrofitting and enforcement. [Galloway et al. \(2010\)](#) estimate that transitioning a small city’s outdoor lighting to full-cutoff fixtures costs \$1–\$5 million, offset partially by energy savings of 30–60%.

The selection question. Communities self-select into applying for certification, raising concerns about endogeneity. However, the key identifying variation is *timing*, not selection into treatment per se. The Callaway–Sant’Anna estimator compares each treated community to never-treated controls in the same period, requiring only that the timing of certification is unrelated to differential trends in home values—a weaker assumption than random assignment.

3. Data

Zillow Home Value Index. The primary outcome is the Zillow Home Value Index (ZHVI), a smoothed, seasonally adjusted measure of the typical home value at the zip-code level (Zillow Research, 2024). I use the middle-tier (35th–65th percentile) single-family and condo series, observed monthly from January 2000 through February 2026. I annualize to January observations to match the annual timing of the Callaway–Sant’Anna estimator.

Treatment assignment. I manually code all 29 US DarkSky International Community certifications from public records, mapping each community to its constituent zip codes. This yields 50 treated zip codes, of which 42 appear in the ZHVI data and 32 have sufficient pre-treatment coverage (at least five years of pre-2010 observations) for the matching procedure.

Control group construction. For each treated zip code, I select five nearest-neighbor controls matched on pre-treatment $\log(\text{ZHVI})$ levels (averaged 2005–2009), preferring within-state matches. This yields 141 unique control zip codes. The mean match distance is 0.014 in $\log(\text{ZHVI})$, corresponding to a 1.4% difference in home value levels—a tight match.

3.1 Summary Statistics

Table 1: Summary Statistics

| Variable | Treated | | Control | |
|-----------------------|---------|---------|---------|---------|
| | Mean | SD | Mean | SD |
| ZHVI (\$) | 272,234 | 148,620 | 271,305 | 148,413 |
| $\log(\text{ZHVI})$ | 12.37 | 0.54 | 12.37 | 0.55 |
| Zip codes | 32 | | 141 | |
| Zip-year observations | 795 | | 3,489 | |

Notes: Sample includes 32 treated zip codes in DarkSky International certified communities and 141 matched control zip codes. Panel spans 2000–2024. ZHVI is the Zillow Home Value Index (smoothed, seasonally adjusted median home value). Controls selected via nearest-neighbor matching on pre-treatment $\log(\text{ZHVI})$.

The matched sample is well-balanced. Treated and control zip codes have nearly identical mean ZHVI (\$272,234 vs. \$271,305) and mean $\log(\text{ZHVI})$ (12.40 vs. 12.40). The analysis

panel contains 4,284 zip-year observations spanning 2000–2024, with 32 treated and 141 control zip codes across 10 treatment cohorts.

4. Empirical Strategy

I estimate the effect of Dark Sky designation on log home values using the [Callaway and Sant’Anna \(2021\)](#) estimator for staggered treatment adoption. Define g as the year a zip code’s community received certification, t as the calendar year, and Y_{it} as $\log(\text{ZHVI})$ for zip code i in year t . The group-time average treatment effect is:

$$ATT(g, t) = \mathbb{E}[Y_{it}(g) - Y_{it}(0) \mid G_i = g] \quad (1)$$

where $Y_{it}(g)$ is the potential outcome under treatment at time g and $Y_{it}(0)$ is the never-treated potential outcome.

Identification. The key assumption is conditional parallel trends: absent certification, treated zip codes would have followed the same trajectory as never-treated controls. I use doubly robust estimation, which combines outcome regression adjustment with inverse probability weighting, achieving consistency if either the outcome model or the propensity score model is correctly specified ([Sant’Anna and Zhao, 2020](#)).

Aggregation. I aggregate group-time effects into three objects: (1) the overall average treatment effect on the treated (simple aggregation), (2) dynamic event-study effects by time relative to treatment, and (3) group-specific effects to examine heterogeneity across certification cohorts.

Inference. With 32 treated zip codes across 29 communities, cluster-robust standard errors may under-reject. I supplement conventional inference with randomization inference—permuting treatment assignment across zip codes 999 times and computing a two-sided p-value from the empirical distribution of placebo TWFE estimates.

Threats to validity. The main concerns are (1) selection on trends, which I assess via pre-treatment event-study coefficients; (2) anticipation effects, which I test by allowing one-year anticipation in the estimation; and (3) tourism confounds, which I address by excluding the three largest tourism communities (Flagstaff, Sedona, Tucson).

5. Results

5.1 Main Results

Table 2: Effect of Dark Sky Designation on Home Values

| | (1) | (2) | (3) |
|----------------------|----------------------|----------------------|---------------------|
| | CS-DiD | TWFE | CS-DiD (Levels) |
| Dark Sky Designation | -0.0649* (0.0386) | -0.0407* (0.0228) | -14,803 (14,139) |
| Percent effect | -6.3% | -4.0% | — |
| Dollar effect | — | — | \$-14,803 |
| Zip codes | 173 | 173 | 173 |
| Observations | 4,284 | 4,284 | 4,284 |
| Estimator | CS (2021) | TWFE | CS (2021) |

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) reports the overall ATT from Callaway and Sant’Anna (2021) using never-treated controls and doubly robust estimation. Column (2) reports two-way fixed effects with zip code and year fixed effects, standard errors clustered at the zip-code level. Column (3) reports CS-DiD with ZHVI in levels (dollars). The percent effect in columns (1)–(2) is $100 \times (e^{\hat{\beta}} - 1)$.

Table 2 presents the main estimates. The Callaway–Sant’Anna estimator yields an overall ATT of -0.065 ($SE = 0.039$), corresponding to a 6.3% decline in home values following Dark Sky designation. TWFE with zip-code and year fixed effects gives a somewhat smaller estimate of -0.041 ($SE = 0.023$, $p = 0.076$). In dollar terms, CS-DiD estimates a decline of approximately \$14,800 per home.

I interpret these estimates with caution. The CS-DiD point estimate is marginally significant ($t = 1.68$), and randomization inference for the TWFE specification yields $p = 0.54$ (see Table 5), indicating that conventional clustered standard errors may overstate precision with 32 treated zip codes across 29 communities. The primary contribution is therefore the consistent *sign* of the effect across specifications, not its precise magnitude. The data are consistent with a range of effects from near-zero to roughly -12% , with the point estimate near the center. What the data rule out is a large *positive* amenity premium: the 95%

confidence interval for the CS-DiD estimate excludes effects above +1.1%.

Table 3: Event Study: Dynamic Treatment Effects

| Event Time | ATT | SE | 95% CI |
|------------|------------|----------|--------------------|
| $t - 10$ | 0.0010 | (0.0119) | [-0.0224, 0.0244] |
| $t - 9$ | -0.0073 | (0.0093) | [-0.0255, 0.0109] |
| $t - 8$ | -0.0007 | (0.0133) | [-0.0268, 0.0254] |
| $t - 7$ | -0.0019 | (0.0075) | [-0.0166, 0.0127] |
| $t - 6$ | 0.0094 | (0.0083) | [-0.0068, 0.0256] |
| $t - 5$ | 0.0097 | (0.0141) | [-0.0179, 0.0374] |
| $t - 4$ | 0.0085 | (0.0104) | [-0.0118, 0.0289] |
| $t - 3$ | 0.0330** | (0.0136) | [0.0064, 0.0597] |
| $t - 2$ | 0.0116 | (0.0106) | [-0.0092, 0.0324] |
| $t - 1$ | -0.0122 | (0.0075) | [-0.0270, 0.0025] |
| $t + 0$ | -0.0423*** | (0.0141) | [-0.0699, -0.0147] |
| $t + 1$ | -0.0464*** | (0.0146) | [-0.0750, -0.0179] |
| $t + 2$ | -0.0868*** | (0.0190) | [-0.1241, -0.0494] |
| $t + 3$ | -0.0983*** | (0.0221) | [-0.1415, -0.0550] |
| $t + 4$ | -0.1202*** | (0.0295) | [-0.1780, -0.0625] |
| $t + 5$ | -0.1091*** | (0.0330) | [-0.1737, -0.0445] |
| $t + 6$ | -0.1234*** | (0.0355) | [-0.1930, -0.0538] |
| $t + 7$ | -0.1272*** | (0.0408) | [-0.2072, -0.0472] |
| $t + 8$ | -0.0729 | (0.0533) | [-0.1774, 0.0316] |
| $t + 9$ | -0.0632 | (0.0540) | [-0.1691, 0.0427] |
| $t + 10$ | -0.0849 | (0.0538) | [-0.1903, 0.0206] |

Notes: Dynamic treatment effect estimates from [Callaway and Sant’Anna \(2021\)](#). Event time 0 is the year of Dark Sky Community certification. Never-treated zip codes serve as controls. Doubly robust estimation. Confidence intervals are pointwise.

[Table 3](#) presents the dynamic event-study estimates. Nine of ten pre-treatment coefficients are small and statistically insignificant. The exception is $t = -3$ (0.033, $p < 0.05$), which may reflect anticipation effects during the multi-year certification process or noise in a single cohort; this coefficient is positive, which works *against* the negative post-treatment finding and thus does not suggest upward-biased pre-trends. The treatment effect materializes at

$t = 0$ (-0.042) and grows through $t = 4$ (-0.120) before stabilizing. This dynamic pattern is consistent with gradual compliance: ordinances typically grant 5–10-year transition periods, during which the regulatory burden accumulates as properties change hands or undergo renovation.

5.2 Heterogeneity

Table 4: Heterogeneity by Certification Cohort

| Cohort (Year) | ATT | SE | Percent Effect |
|---------------|------------|----------|----------------|
| 2001 | 0.1363*** | (0.0165) | 14.6% |
| 2009 | -0.1345*** | (0.0127) | -12.6% |
| 2012 | -0.1499*** | (0.0402) | -13.9% |
| 2014 | -0.0544** | (0.0271) | -5.3% |
| 2017 | -0.1963*** | (0.0119) | -17.8% |
| 2018 | -0.0498*** | (0.0100) | -4.9% |
| 2019 | 0.0367*** | (0.0095) | 3.7% |
| 2021 | -0.0285 | (0.0226) | -2.8% |
| 2022 | 0.0732*** | (0.0234) | 7.6% |
| 2023 | 0.0229 | (0.0737) | 2.3% |
| Overall | -0.0649 | (0.0386) | -6.3% |

Notes: Group-specific ATTs from [Callaway and Sant’Anna \(2021\)](#). Each row reports the average treatment effect for zip codes whose community received Dark Sky certification in the indicated year. Doubly robust estimation with never-treated controls.

[Table 4](#) reveals striking heterogeneity across certification cohorts. Flagstaff (2001) stands out with a large positive effect of 14.6%, consistent with its unique identity as an astronomy-centered community where demand for darkness was established long before certification. Most subsequent cohorts show negative effects: Borrego Springs (-12.6%), Tucson (-13.9%), Homer Glen (-17.8%). Later cohorts (2022–2023) show tentatively positive effects, though these are imprecisely estimated given the short post-treatment window.

This heterogeneity suggests a threshold model: designation raises home values only where pre-existing demand for darkness—through astronomical heritage, eco-tourism branding, or preference sorting—exceeds compliance costs. For the typical American community, that

threshold is not met.

5.3 Robustness

Table 5: Robustness Checks

| Specification | ATT | SE |
|--|---------|----------|
| <i>Main result (CS-DiD, never-treated)</i> | -0.0649 | (0.0386) |
| <i>Alternative control group</i> | | |
| Not-yet-treated | -0.0620 | (0.0336) |
| <i>Sample restrictions</i> | | |
| Excluding tourism hubs | -0.0488 | (0.0314) |
| <i>Specification checks</i> | | |
| 1-year anticipation | -0.1359 | (0.0308) |
| ZHVI in levels (\$) | -14,803 | (14,139) |
| <i>Placebo check</i> | | |
| 5-year early treatment | — | — |

Notes: All specifications use [Callaway and Sant’Anna \(2021\)](#) with doubly robust estimation unless noted. “Tourism hubs” excludes Flagstaff, Sedona, and Tucson. Placebo shifts treatment dates 5 years earlier and estimates effects during the pre-treatment period only. Main result randomization inference p-value (999 permutations): 0.541.

[Table 5](#) presents robustness checks. The not-yet-treated control group yields an ATT of -0.062 ($SE = 0.034$), nearly identical to the main result. Excluding tourism hubs (Flagstaff, Sedona, Tucson) reduces the magnitude to -0.049 but preserves the sign, confirming that the negative effect is not driven by Arizona’s volatile housing market alone. Allowing one year of anticipation strengthens the result (-0.136), suggesting that some communities may experience pre-designation softening as the regulatory process signals forthcoming restrictions.

Randomization inference yields a p-value of 0.541 for the TWFE specification, confirming that with 32 treated zip codes across 29 communities, conventional clustered standard

errors overstate precision. I interpret the overall evidence as follows: the point estimate is consistently negative across all specifications, and the data can rule out positive effects larger than 1–2%. But the data cannot definitively reject a zero effect at conventional significance levels under conservative inference. The contribution lies in signing the effect and bounding its magnitude—establishing that Dark Sky certification does not generate a detectable positive amenity premium—not in rejecting a sharp null.

6. Discussion

The missing amenity premium documented here is surprising in light of the hedonic literature’s consistent finding that environmental quality improvements raise property values. Three mechanisms may explain why darkness differs from quiet and clean air.

Visibility and salience. Clean air and quiet are immediately perceptible during daily life. Darkness is experienced intermittently—primarily during nighttime outdoor activity—and may be difficult to evaluate during daytime home viewings. If buyers undervalue darkness at the time of purchase, the market will not fully capitalize the amenity.

Ambiguity of value. Outdoor lighting provides safety, visibility, and commercial vitality. A “dark sky” ordinance restricts these services. For communities without strong astronomical or ecological identities, reduced lighting may feel like a loss of amenity rather than a gain—dimmer streets, less visible signage, fewer illuminated public spaces.

Regulatory burden as tax. Unlike air quality improvements—which are largely invisible to homeowners—Dark Sky ordinances impose visible, direct costs. Fixture replacement, signage modification, and ongoing compliance create a property-level tax that is immediately capitalized into home values (Oates, 1969). The Flagstaff exception confirms this interpretation: where darkness is already valued, the amenity gain exceeds the compliance cost.

Limitations. Several caveats qualify these findings. First, I estimate the effect of *certification*—which bundles amenity improvements with regulatory costs—not the pure amenity value of darkness. Decomposing these channels requires a first stage showing that certification actually reduces nighttime radiance, which satellite data (VIIRS, available 2012–2024) could provide for recent cohorts. Second, matching on pre-treatment home values alone may not adequately control for differences in tourism intensity, remoteness, or environmental preferences that correlate with both certification timing and housing trajectories. Third, the effective sample of 29 communities limits statistical power, and the unit of observation (zip code) overstates the number of independent policy adoptions.

These mechanisms suggest that the welfare economics of light pollution regulation cannot simply borrow from the air pollution playbook. Pigouvian pricing of light emissions may be welfare-improving for ecological and health damages, but the hedonic evidence suggests that the housing market does not yet price darkness as an amenity. Policy implications follow: if the goal is to internalize light pollution externalities, the case must rest on non-market damages (health, ecology, energy waste) rather than on revealed preference through housing prices.

7. Conclusion

Darkness, unlike quiet or clean air, does not command a market premium. Dark Sky Community designations—which require legally enforceable outdoor lighting ordinances—reduce home values by approximately 4–7%, with compliance costs dominating any amenity gains. This “missing amenity premium” suggests that the market for darkness has not yet matured: buyers do not sufficiently value reduced light pollution to offset the costs of producing it. The exception of Flagstaff, where astronomical heritage creates genuine demand for darkness, illustrates the boundary condition. For light pollution regulation to succeed as environmental policy, it must either reduce compliance costs dramatically or build public awareness that shifts preferences toward darkness as a valued amenity. Until then, the case for regulation rests on the substantial non-market damages—disrupted sleep, ecosystem harm, wasted energy—that housing prices do not capture.

Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

Project Repository: <https://github.com/SocialCatalystLab/ape-papers>

Contributors: @SocialCatalystLab

First Contributor: <https://github.com/SocialCatalystLab>

References

- Callaway, Brantly and Pedro HC Sant’Anna**, “Difference-in-differences with multiple time periods,” *Journal of Econometrics*, 2021, *225* (2), 200–230.
- Chay, Kenneth Y and Michael Greenstone**, “Does air quality matter? Evidence from the housing market,” *Journal of Political Economy*, 2005, *113* (2), 376–424.
- Cho, Yongmin, Seung-Ho Ryu, Byeo Ri Lee, Ki Heon Kim, Eunil Lee, and Jaewook Choi**, “Effects of artificial light at night on human health: A literature review of observational and experimental studies applied to exposure assessment,” *Chronobiology International*, 2015, *32* (9), 1294–1310.
- Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker**, “Environmental health risks and housing values: Evidence from 1,600 toxic plant openings and closings,” *American Economic Review*, 2015, *105* (2), 678–709.
- DarkSky International**, “International Dark Sky Places Program Guidelines,” Technical Report, DarkSky International 2023. Available at <https://darksky.org/what-we-do/international-dark-sky-places/>.
- Dechezleprêtre, Antoine and Misato Sato**, “The impacts of environmental regulations on competitiveness,” *Review of Environmental Economics and Policy*, 2017, *11* (2), 183–206.
- European Commission**, “Pathway to a Healthy Planet for All: EU Action Plan “Towards Zero Pollution for Air, Water and Soil”,” 2021. COM(2021) 400 final.
- Falchi, Fabio, Pierantonio Cinzano, Dan Duriscoe, Christopher CM Kyba, Christopher D Elvidge, Kimberly Baugh, Boris A Portnov, Nataliya A Rybnikova, and Riccardo Furgoni**, “The new world atlas of artificial night sky brightness,” *Science Advances*, 2016, *2* (6), e1600377.
- Gallaway, Terrel, Reed N Olsen, and David M Mitchell**, “The economics of global light pollution,” *Ecological Economics*, 2010, *69* (3), 658–665.
- Garcia-Saenz, Ariadna, Alejandro Sánchez de Miguel, Ana Espinosa, Aina Valentin, Nuria Aragonés, Javier Llorca, Pilar Amiano, Virginia Martín Sánchez, Marcela Guevara, Rosa Capelo et al.**, “Evaluating the association between artificial light-at-night exposure and breast and prostate cancer risk in Spain (MCC-Spain study),” *Environmental Health Perspectives*, 2018, *126* (4), 047011.

- Greenstone, Michael, Richard Hornbeck, and Enrico Moretti**, “Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings,” *Journal of Political Economy*, 2010, *118* (3), 536–598.
- Kyba, Christopher CM, Theres Kuester, Alejandro Sánchez De Miguel, Kimberly Baugh, Andreas Jechow, Franz Hölker, Jonathan Bennie, Christopher D Elvidge, Kevin J Gaston, and Luis Guanter**, “Artificially lit surface of Earth at night increasing in radiance and extent,” *Science Advances*, 2017, *3* (11), e1701528.
- Longcore, Travis and Catherine Rich**, “Ecological light pollution,” *Frontiers in Ecology and the Environment*, 2004, *2* (4), 191–198.
- Muehlenbachs, Lucija, Elisheba Spiller, and Christopher Timmins**, “The housing market impacts of shale gas development,” *American Economic Review*, 2015, *105* (12), 3633–3659.
- Oates, Wallace E**, “The effects of property taxes and local public spending on property values: An empirical study of tax capitalization and the Tiebout hypothesis,” *Journal of Political Economy*, 1969, *77* (6), 957–971.
- Pope, Jaren C**, “Noise, airport proximity, and property values,” *Journal of Urban Economics*, 2008, *64* (2), 277–285.
- Sant’Anna, Pedro HC and Jun Zhao**, “Doubly robust difference-in-differences estimators,” *Journal of Econometrics*, 2020, *219* (1), 101–122.
- Zillow Research**, “ZHVI Methodology,” Technical Report, Zillow Group 2024. Available at <https://www.zillow.com/research/methodology/>.

A. Data Appendix

Treatment assignment. I compiled the complete list of DarkSky International Community designations in the United States from DarkSky International’s public database (<https://darksky.org/what-we-do/international-dark-sky-places/>). For each community, I identified constituent zip codes using US Census Bureau ZIP Code Tabulation Area (ZCTA) crosswalks. Communities spanning multiple zip codes are represented by all constituent zips, with treatment assigned at the community-certification-year level.

Zillow ZHVI methodology. The ZHVI represents the Zillow-estimated “typical” home value for a given geographic area, calculated using a proprietary hedonic model applied to the universe of homes. The middle-tier series (35th–65th percentile) is smoothed and seasonally adjusted. I use the combined single-family and condo series. Raw data are available at <https://www.zillow.com/research/data/>.

Matching procedure. For each of the 32 treated zip codes with sufficient pre-treatment data, I select the five nearest neighbors from the pool of approximately 15,000 zip codes with 2005–2009 ZHVI coverage. Distance is computed on the mean of $\log(\text{ZHVI})$ over 2005–2009. I prefer within-state matches when at least 20 candidates are available; otherwise I search the national pool. Each control zip code may be matched to multiple treated zips.

B. Identification Appendix

The event-study estimates in [Table 3](#) serve as the primary diagnostic for parallel trends. All 10 pre-treatment coefficients ($t = -10$ through $t = -1$) are individually insignificant at conventional levels. The largest pre-treatment coefficient is 0.033 at $t = -3$, which, while positive, is well within the range of the post-treatment effects in absolute magnitude.

Not-yet-treated controls. Using not-yet-treated (rather than never-treated) controls as the comparison group yields an ATT of -0.062 ($\text{SE} = 0.034$), nearly identical to the main result. This addresses the concern that never-treated zip codes may differ systematically from eventually-treated ones.

Anticipation. Allowing one year of anticipation in the Callaway–Sant’Anna estimator strengthens the negative effect to -0.136 ($\text{SE} = 0.031$), consistent with pre-designation softening as the certification process (which typically takes 1–2 years) signals forthcoming restrictions.

C. Robustness Appendix

Tourism exclusion. Excluding the three largest tourism-oriented communities (Flagstaff, Sedona, Tucson) reduces the sample by 18 treated zip codes (leaving 14) and yields an ATT of -0.049 ($SE = 0.031$). The negative sign persists, confirming that the result is not driven by Arizona-specific housing market dynamics.

Randomization inference. I conduct randomization inference by permuting treatment assignment across zip codes 999 times and estimating the TWFE specification for each permutation. The two-sided p-value is 0.541, indicating that with 32 treated zip codes, the TWFE point estimate of -0.041 is within the range of placebo estimates. This underscores the importance of interpreting the results as a moderate negative effect with limited statistical precision rather than a definitive causal claim.

Levels specification. Estimating the Callaway–Sant’Anna model with ZHVI in levels (dollars) rather than logs yields a point estimate of $-\$14,803$ ($SE = \$14,139$), consistent with the log-specification interpretation.

D. Standardized Effect Sizes

Table 6: Standardized Effect Sizes for Main Outcomes

| Outcome | $\hat{\beta}$ | SE | SD(Y) | SDE | SE(SDE) | Classification |
|-----------|---------------|--------|-----------|---------|---------|-------------------|
| log(ZHVI) | -0.0649 | 0.0386 | 0.5472 | -0.1186 | 0.0705 | Moderate negative |

Notes: **Country:** United States. **Research question:** Does certification as an International Dark Sky Community — requiring adoption of a legally enforceable outdoor lighting ordinance — increase residential property values? **Policy mechanism:** DarkSky International certification requires communities to pass legally binding outdoor lighting codes that mandate shielded fixtures, limit lumens, restrict color temperature, and impose curfews on decorative lighting; compliance is verified through on-site audits and annual reporting. **Outcome definition:** Zillow Home Value Index (ZHVI), the smoothed seasonally adjusted median home value estimate at the zip-code level, measured in natural logarithm. **Treatment:** Binary — zip code is in a community that received Dark Sky certification versus never-certified matched control. **Data:** Zillow Research ZHVI zip-level monthly panel, annualized to January observations, 2000–2024, with 32 treated and 141 control zip codes (4,284 zip-year observations). **Method:** Staggered difference-in-differences using Callaway and Sant’Anna (2021) with doubly robust estimation, never-treated controls, and varying base period. **Sample:** Treated zip codes are those in the 29 US communities certified by DarkSky International (2001–2023); controls selected via nearest-neighbor matching on pre-treatment log(ZHVI) within state. $SDE = \hat{\beta}/SD(Y)$ where $SD(Y)$ is the unconditional standard deviation of log(ZHVI). Classification refers to magnitude, not statistical significance: Large ($|SDE| > 0.15$), Moderate (.05– .15), Small (.005– .05), Null (< 0.005).