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Sara Suarez-Fernandez
Manuel Arrigo
Carlos Gomez-Gonzalez
Markus Lang

Departamento de Economía

Universidad de Oviedo

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Sport stadiums and urban economic development: Evidence from nightlight data in Europe

Sara Suarez-Fernandez
Faculty of Economics and Business
University of Oviedo
suarezfsara@uniovi.es

Manuel Arrigo
Faculty of Social and Political Sciences
University of Lausanne
manuel.arrigo@unil.ch

Carlos Gómez-González
Faculty of Social and Political Sciences
University of Lausanne
carlos.gomez@unil.ch

Markus Lang
Faculty of Social and Political Sciences
University of Lausanne
markus.lang@unil.ch

Abstract

This paper investigates the local economic impact of new sports stadiums using high-frequency, high-resolution nighttime light (NTL) satellite imagery. Unlike previous studies relying almost exclusively on annual aggregated outcomes over broad spatial units, we exploit monthly and daily NTL data matched to census-level administrative units to distinguish persistent changes in local activity from episodic fluctuations. We examine four newly constructed stadiums in Spain, France, and England, all built on entirely new sites between 2015 and 2020. Our Difference-in-differences and event-study estimates show a consistent and statistically significant increase in localized NTL intensity following stadium inaugurations, characterized by a pronounced spatial decay. Notably, this increase is not driven by match-day activity; rather, it reflects a structural revitalization of the immediate urban vicinity. These patterns are robust to a series of checks using daily data, including controls for match-day activity, alternative buffer definitions, the exclusion of extreme luminosity values, and alternative event-day measures. Overall, the results suggest that stadiums function as localized, multi-purpose urban nodes that generate intermittent economic activation rather than broad-based urban regeneration. More generally, the results highlight the value of fine temporal and spatial data for identifying infrastructure externalities that aggregated measures may overlook.

Keywords: urban regeneration, sports economics, nighttime lights, difference-in-differences, agglomeration externalities

JEL codes: R12, R53, R58, L83

1. Introduction

The construction of a new major sports stadium is a highly debated and politically charged infrastructure investment for modern cities (Bradbury et al., 2024; Noble & Agini, 2024). New stadium projects entail substantial financial costs, often exceeding hundreds of millions of euros; a trend that seems to be accelerating in recent years (Haskel et al., 2024; Moore, 2024). Policymakers frequently justify these investments on the grounds of local economic development, neighborhood revitalization, and increased commercial activity. However, whether these benefits materialize in practice remains an open empirical question, with direct implications for urban policy (Bradbury et al., 2024).

A substantial body of the literature has examined the impact of sports stadiums. The prevailing consensus points to null findings, as economists have largely concluded that stadiums generate little to no net economic benefit and constitute low-return public investments (Matheson, 2019; Bradbury et al., 2023). Most studies consistently report no significant effect of professional sports stadiums and sport facilities on local economic growth (Siegfried & Zimbalist, 2006; Coates, 2007), and some metropolitan areas even experienced declines in per capita income (Coates & Humphreys, 2008). Similarly, research focusing on stadium investments made for large events, such as the FIFA World Cup, fails to identify widespread positive effects on income or employment (Feddersen et al., 2009). However, a smaller strand of the literature suggests that positive effects may emerge when accounting for local heterogeneities (Santo, 2005) and focusing on more spatially concentrated outcomes, such as commercial activity in the immediate vicinity of venues (Ahlfeldt & Maennig, 2010; Harger et al., 2016; Abbiasov & Sedov, 2023), residential housing values (Ahlfeldt & Kavetsos, 2014; Feng & Humphreys, 2018; Funahashi & Cardazzi, 2026), and, in some cases, local full-service restaurants (Depken and Fore, 2020).

An underexamined aspect of this literature is its reliance on annual data aggregated over relatively broad spatial units, which may overlook episodic and spatially concentrated spillover effects. Examining these patterns with finer spatial and temporal granularity is key to developing a more complete understanding of how new stadiums may generate local economic activity and under which conditions such effects emerge, thereby helping to inform urban policy. As agglomeration externalities are strongest in the immediate vicinity of their source and attenuate rapidly with distance (Rosenthal & Strange, 2020), we expect the economic footprint of a stadium to decay rapidly with distance from the venue. Research also suggests that modern stadium infrastructure is designed to serve as a catalytic urban anchor rather than a mere venue for cyclical sporting events (Rosentraub, 2014), but the economic footprint of this type of sport infrastructure is likely tied to its event calendar.

Capturing effects of this kind, spatially concentrated and episodic, requires data at a finer spatial and temporal resolution than the annually aggregated statistics on which most of this literature relies. Remotely sensed nighttime light (NTL) satellite data offer one such alternative. As Donaldson and Storeygard (2016) document in their seminal review, NTL has emerged as a transformative tool for economists, providing high-resolution measures of local activity in settings where conventional indicators are too coarse or too infrequent to detect them. NTL captures the light emitted from the surface at night and has become a widely used proxy for local economic activity, as higher luminosity is associated with greater energy consumption, commercial activity, and human presence (Henderson et al., 2012). Although measures such as local employment rates, business counts, or land prices would provide more direct information on the underlying economic mechanisms (Ahlfeldt & Kavetsos, 2014; Harger et al., 2016; Feng & Humphreys, 2018; Abbiasov & Sedov, 2023; Funahashi & Cardazzi, 2026), they are rarely available at the temporal and spatial resolutions required to capture the potentially localized and episodic effects of new sports stadiums.

By contrast, NTL data are available at daily and monthly frequencies with a 500-meter spatial resolution, and can be consistently employed across cities and countries. As such, they are uniquely suited to studying the economic footprint of sports infrastructure and align with recent advances in spatial economics that exploit high-frequency luminosity data to proxy economic activity (Gibson et al., 2021), particularly in contexts where conventional statistical measures fail to capture the spatial and temporal nuances of economic activity and development (Henderson et al., 2012; Nordhaus & Chen, 2015). Prior research has used it to assess the impact of foreign aid (Dreher et al., 2021), high-speed rail networks (Huang et al., 2024), oil prices (Storeygard, 2016), city hubs (Bluhm & Krause, 2022), measurement and delineation of city size (Bosker et al., 2021; Ch et al., 2021), and cultural policy (Suárez-Fernández et al., 2026), among others. Within the specific domain of sports infrastructure, two prior studies use NTL data. Pfeifer et al. (2018) use a synthetic control design to evaluate 2010 FIFA World Cup investments in South Africa, observing short-term luminosity gains near sports venues and some more durable effects from transportation-related projects. More recently, Lindlacher and Pirich (2025) use a staggered difference-in-differences design to examine the economic impact of Chinese-financed stadiums in Sub-Saharan African countries, finding that stadium completion increases city-level NTL intensity by approximately 24-27% and correlates with positive employment effects in surrounding areas.

Yet both studies leave central questions about the economic footprint of stadiums in mature urban economies open. Pfeifer et al. (2018) and Lindlacher & Pirich (2025) study developing-country contexts, respectively, mega-event investments in South Africa and Chinese-financed venues in Sub-Saharan Africa, where the institutional environment, financing structure, and counterfactual urban trajectory differ markedly from those of European cities. Both also rely on annual luminosity measures aggregated at the city level, which capture average shifts following stadium completion but cannot speak to how effects decay within the city or how they decompose into recurring event-driven spikes and persistent changes in baseline activity. These spatial and temporal dimensions are precisely where the most policy-relevant variation is likely to lie.

Our paper makes three primary contributions to the literature. First, we provide new evidence on the local economic impact of stadium construction in Western and Southern Europe, a context that has received comparatively limited attention relative to the extensive evidence available for the United States (e.g., Bradbury et al., 2023). Existing international evidence remains relatively scarce and has largely focused either on mega-events (Feddersen et al., 2009) or on developing countries (Lindlacher & Pirich, 2025), despite the fact that the mechanisms through which stadiums affect surrounding areas are likely to differ across institutional and economic settings. Second, we contribute to the growing literature using remotely sensed NTL data as a proxy for economic activity (Henderson et al., 2012; Gibson et al., 2021). In contrast to previous studies on sports infrastructure that rely on older generations of satellite sensors or lower-frequency measures (e.g., Pfeifer et al., 2018; Lindlacher & Pirich, 2025), we exploit the high temporal resolution of the new-generation VIIRS sensor to construct monthly and daily measures of localized activity.[1] Third, and most importantly, we provide new insights into the spatial and temporal dynamics of large-scale infrastructure externalities. Previous research has predominantly relied on annual data aggregated over relatively broad geographic units,

[1] This choice is empirically supported by Gibson et al. (2021), who demonstrate that VIIRS serves as a superior proxy for local economic activity compared to legacy DMSP data, thereby validating the suitability of our high-resolution approach within an urban European context. Gibson et al. (2020) also show that the use of legacy DMSP satellite series are very limited for temporal comparisons and small-scale spatial analysis due to problematic sensor calibration and spatial resolution.

potentially overlooking short-lived and highly localized spillovers. While a few studies suggest that stadium effects may be spatially concentrated (Ahlfeldt & Maennig, 2010), little is known about their temporal structure. By combining high-frequency NTL data with a difference-in-differences (DiD) framework, we distinguish between episodic fluctuations and more persistent changes in baseline local activity. This approach provides a novel perspective on the economic footprint and legacy of large-scale sports infrastructure and helps reconcile the null findings reported in much of the existing literature with evidence of highly localized and temporally concentrated effects.

Our sample includes four newly constructed stadiums in Western and Southern Europe, built on sites without prior sports infrastructure, thereby excluding renovations or replacements of older venues. We seek stadiums in areas with administrative census-unit-level data comparable to a standardized 500x500m NTL grid, built between 2013 and 2024. This timeframe is key to using daily and monthly NTL data as the outcome variable.[2] The sample comprises stadiums located in Spain ($n = 1$), France ($n = 2$) and England ($n = 1$). Our identification strategy employs a DiD framework estimated at the census-unit level, a spatial unit more granular than postal code areas. First, we search for control units within the same city for each treated stadium to ensure that treated and control units share similar socioeconomic and urban characteristics. Subsequently, we compare NTL between treated and control units using the DiD estimator. To examine dynamic treatment effects, we employ the event-study estimator developed by Callaway and Sant' Anna (2021). Furthermore, we implement a daily DiD framework, a high-frequency approach that controls for match-day activity to disentangle structural shifts from transient fluctuations associated with stadium events. Finally, we conducted a sensitivity analysis by excluding observations exceeding the 90th percentile of the NTL mean.[3]

Across the four cases, the qualitative pattern is consistent, although effect magnitudes vary substantially, most notably for the Matmut Atlantique, where the low-baseline industrial setting and the UEFA Euro 2016 motivation amplify the estimated impact. While stadium construction generates positive and statistically significant effects on mean NTL, in line with Abbiasov &

[2] The VIIRS sensor was launched in 2012, providing NTL data from 2012 to 2025. To ensure a balanced panel with at least one year of pre- and post-construction data for our difference-in-differences design, we restrict our sample to stadiums completed between 2013 and 2024.

[3] It is important to note that NTL emissions near sports venues can be significantly amplified by specialized grow-light systems. As demonstrated by Geliot et al. (2022), such technical factors can create unusually intense luminosity, which must be carefully accounted for when interpreting satellite-derived data in the vicinity of stadiums.

Sedov (2023) and Lindlacher and Pirich (2025), these impacts appear highly localized and temporally concentrated, characterized by pronounced episodic spikes interspersed with periods of relative stability, which casts doubt on claims of widespread urban regeneration. This pattern suggests that the aggregated annual data commonly used in the existing literature may mask short-lived fluctuations, making them statistically difficult to detect, and highlights the importance of incorporating temporal granularity into studies. Additionally, we observe that these spikes are not primarily driven by sporting matchdays, suggesting that non-match uses of the venue may contribute to localized activation. Overall, our results suggest that stadiums are neither the primary drivers of broad-based urban growth nor devoid of economic impact; rather, they function as multi-purpose hubs that concentrate and stimulate localized economic activity.

2. Data and Spatial Matching

2.1. Data Sources and Spatial Resolution

The panel dataset integrated three categories of data sources: high-resolution satellite imagery, socioeconomic data, and geospatial information on stadiums. These data sources allowed us to compare post-construction NTL trajectories around newly developed stadiums against those of similar control areas that did not receive the infrastructure treatment, conditioning on ex-ante localized demographic characteristics.

First, to capture changes in ground-level luminosity, we exploited remote sensing data of nighttime light (NTL) from the Visible Infrared Imaging Radiometer Suite Day/Night Band (VIIRS DNB) sensor. The VIIRS DNB sensor is aboard the Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite, a joint NASA/NOAA mission since 2012 (Román et al., 2018). The sensor offers substantial technological advancements over the legacy Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS). Crucially, VIIRS DNB provides a significantly higher spatial resolution, approximately 750 meters versus the 2.7 kilometers of DMSP-OLS, and features in-flight calibration that prevented the severe pixel saturation common in urban cores under older sensors (Evige et al., 2017). Furthermore, its wider dynamic range and superior low-light sensitivity drastically reduced the "blooming effect" (artificial light bleeding into dark pixels), providing a substantially cleaner and more precise measure of ground-level radiometric radiance (Gibson et al., 2021).

Second, we used administrative data at the census level obtained from the official statistical institutes of each respective country: Census Sections for Spain (Instituto Nacional de Estadística, INE), IRIS (Ilots Regroupés pour l'Information Statistique) for France (Institut National de la Statistique et des Études Économiques, INSEE), and LSOAs (Lower Layer Super Output Areas) for England (Office for National Statistics, ONS). These administrative boundaries represent the most granular proxy data available in the immediate vicinity of each sports stadium and allowed us to control for baseline local socioeconomic conditions.

Third, we collected the exact spatial coordinates, construction timelines, and technical specifications of the sports infrastructures from administrative online records and crowdsourced geospatial data from OpenStreetMap (OSM). We used major stadium infrastructures newly constructed between 2013 and 2024 to ensure that the infrastructure shock occurred entirely within the VIIRS temporal window, establishing a clean ex-ante NTL baseline in 2012. Our sample includes stadiums built in Spain, France, and England,[4] countries that belong to the Big Five European football leagues, which generate high levels of economic revenue and competitive prestige. Table 1 presents the sample of sports stadiums analyzed.

Table 1. Newly constructed stadiums in England, France, and Spain.

Stadium	City	Inauguration	Home Team	League	Capacity
Matmut Atlantique	Bordeaux	23-05-2015	Girondins de Bordeaux	Ligue 1	42,115
Groupama Stadium	Lyon	9-01-2016	Olympique Lyonnais	Ligue 1	59,186
Riyadh Air Metropolitano	Madrid	16-09- 2017	Atlético de Madrid	LaLiga	70,460
Gtech Community	London	1-09-2020	Brentford Football Club	Premier League	17,250

Notes: Although currently relegated, FC Girondins de Bordeaux maintained Ligue 1 status throughout the sample period, ensuring its classification as an elite infrastructure.

[4] Although other major facilities were inaugurated within this period, notably the Stade de la Tuilière (home to FC Lausanne-Sport) in Switzerland (2020) and the Europa-Park Stadion (home to SC Freiburg) in Germany (2021), these were excluded from our sample. This decision is driven by cross-national data architecture; while our analysis relies on matching census-unit level data to a standardized 500x500m NTL grid, the subnational data available for Switzerland and Germany are provided on a 100x100m grid. Given that this grid structure is not comparable to the administrative census units defined for our identification strategy, these stadiums were omitted to preserve methodological homogeneity.

2.2. Spatial Matching Procedure

The fundamental objective of our empirical strategy is to isolate the causal impact of stadium construction from confounding localized development trends. To achieve this, the first step was to identify valid control units via Nearest Neighbor Matching based on a vector of baseline socioeconomic and geographic attributes, following Abadie and Imbens (2006, 2011). This non-parametric approach ensures that each treated census unit containing a sports stadium is matched with an empirically optimal control area prior to the infrastructure shock.

To operationalize the matching mechanism, the algorithm conditioned on a multi-dimensional vector of ex-ante covariates (X_i) measured at the baseline period. These covariates captured the initial socioeconomic characteristics of the census units. By minimizing the Mahalanobis distance, we identified control units that mirrored the structural features of our treated areas while remaining unexposed to stadium infrastructure.

For the matching covariates, we used administrative data from the 2011 National Census for Spain and England[5] and from the 2012 National Census for France. This timing ensures the matching process predates all infrastructure shocks, as all stadiums were inaugurated after 2015. Table 2 synthesizes the baseline profiles for each treated stadium unit and its nearest-neighbor ($k = 1$) control unit. Since the matching protocol paired each treated unit with a unique control, traditional t-tests were inapplicable. Instead, we validated baseline parallelism through two criteria. First, the global Average Treatment Effect (ATE) coefficients for the regional pools, reported in the table header of each case study, were statistically indistinguishable from zero ($p > 0.10$), with the London pool being the closest case ($p = 0.11$). Second, the direct numerical convergence of granular covariates (e.g., population/housing density, foreign population, and tenancy structures) across each pair empirically validated their comparability, ensuring that the controls served as valid proxies for the counterfactual trajectories.

[5] Socioeconomic variables for France and Spain are from the 2011 census, while NTL data starts in 2012. Given that census are decennial and VIIRS NTL became operational in 2012, we assume these baseline characteristics are stable and representative of the 2012 pre-treatment period. This minor temporal misalignment is unlikely to introduce significant bias, as structural socioeconomic features exhibit high persistence over such a short interval.

Table 2. Baseline Covariate Profiles and Diagnostic Validation for Matched Controls

Case Study Unit Type	NTL Mean	Pixels (N)	Populat. Density	Foreign (%)	Rented (%)	Housing Density	Additional Variables
Matmut Atlantique Bordeaux (N = 17) ATE: -7.66 (p-value: 0.663)							
Treated 330630101	21.54	90	0.14	0.00%	0.00%	0.00	Employed (%) 0.00%
Control 334490111	4.26	95	0.00	0.00%	0.00%	0.00	Employed (%) 0.00%
Groupama Stadium Lyon (N = 765) ATE: -15.09 (p-value: 0.566)							
Treated 692750112	29.08	24	47.54	9.41%	6.72%	12.76	Employed (%) 87.06%
Control 690270101	26.02	26	202.81	7.02%	9.63%	81.05	Employed (%) 88.30%
Riyadh Air Metropolitano Madrid (N = 1,947) ATE: 3.18 (p-value: 0.680)							
Treated 2807920067	12.46	78	103.77	5.02%	11.36%	35.26	University (%) 33.20%
Control 2807910158	19.97	76	206.83	1.39%	11.98%	68.67	University (%) 25.25%
Gtech Community London (N = 922) ATE: 26.54 (p-value: 0.113)							
Treated E01002566	89.56	6	1437.50	37.75%	17.66%	719.79	—
Control E01001899	66.60	11	1206.25	38.81%	18.70%	583.52	—

Notes: The total number of available candidate administrative units in each regional matching pool (N) is reported next to each case header.

We used a set of spatial and socioeconomic covariates to ensure an appropriate matching control for baseline local characteristics. The vector included: (i) *NTL Mean*, which captures the initial average nighttime light as a proxy for baseline economic development; (ii) *Pixels (N)*, representing the total count of satellite pixel footprints within the unit to account for geographic scale; note that each individual pixel covers an area of approximately 750m x 750m (0.16km^2), and this metric serves to calculate the total physical surface of each unit. (iii) *Population Density* and (iv) *Housing Density*, which reflect the number of people and housing units, both standardized by dividing the total population and housing units by the unit's physical area derived from satellite footprints (N Pixels x 0.16km^2); (v) *Foreign Population (%)*, calculated as the ratio of foreign-nationality residents to the total population to capture demographic diversity; and (vi) *Rented Dwellings (%)*, defined as the proportion of rented housing units over total dwellings to proxy for local real estate tenancy structures. Finally, we incorporated country-specific controls to account for local socioeconomic profiles. Given data constraints across national statistical offices, in Spain, we incorporate the (vii) *Percentage of Higher Education Graduates (University, %),* while in France, we use the *Employment Rate (Employed, %)*.

To ensure counterfactual validity, we refined our matching pools by excluding units with missing covariates (final counts: 1,947 in Madrid; 765 in Lyon). For Bordeaux, we restricted the pool to industrial IRIS typologies (n=17) to match the Matmut Atlantique's specific urban profile. In London, we limited our sample to 922 West London LSOAs, mitigating bias by excluding the extreme scale and density of the wider metropolitan area.

Figure 1 illustrates the evolution of the monthly NTL mean from 2012 to 2025. The solid line represents the treated stadium area, whereas the dashed line corresponds to the matched control unit. As observed, although absolute NTL levels differ across certain locations, the underlying trajectories remain consistent, showing parallel pre-treatment trends. Conversely, a structural divergence emerges following the stadium inauguration. While the control group maintains its initial trend, the treated areas exhibit a marked increase in NTL volatility, with frequent, pronounced spikes in intensity that reveal episodic increases in local nighttime activity following the inauguration.

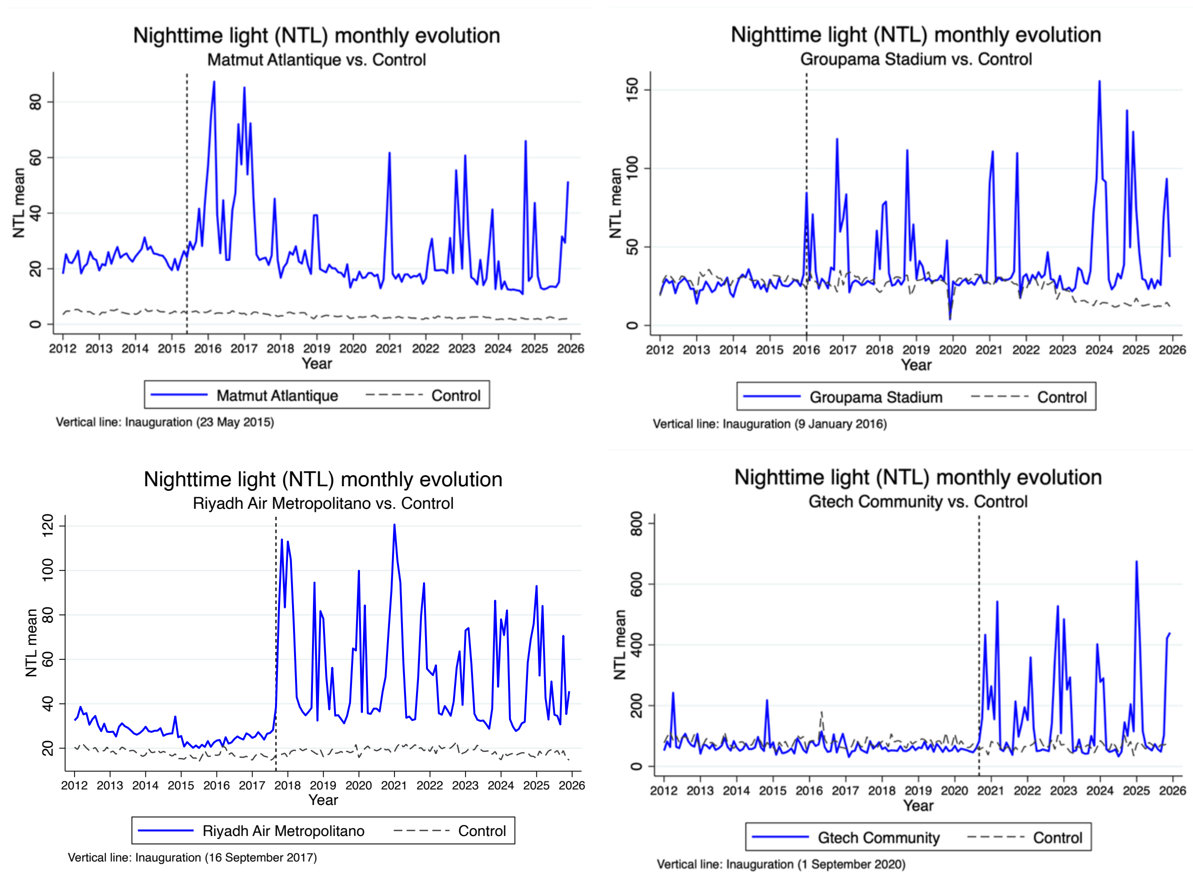

Figure 1. Nighttime light (NTL) monthly evolution: Treated vs. Control units.

Figure 2 displays daily data within a three-year window (one year pre- and two years post-inauguration) and further reinforces the above-mentioned pattern. The high-frequency data reveal significantly greater volatility, with peak intensity values reaching magnitudes hundreds of times higher than the minimum. Notably, at the Gtech Community Stadium in London, the data show distinct periods of stable, low-intensity light that coincide with the off-season.

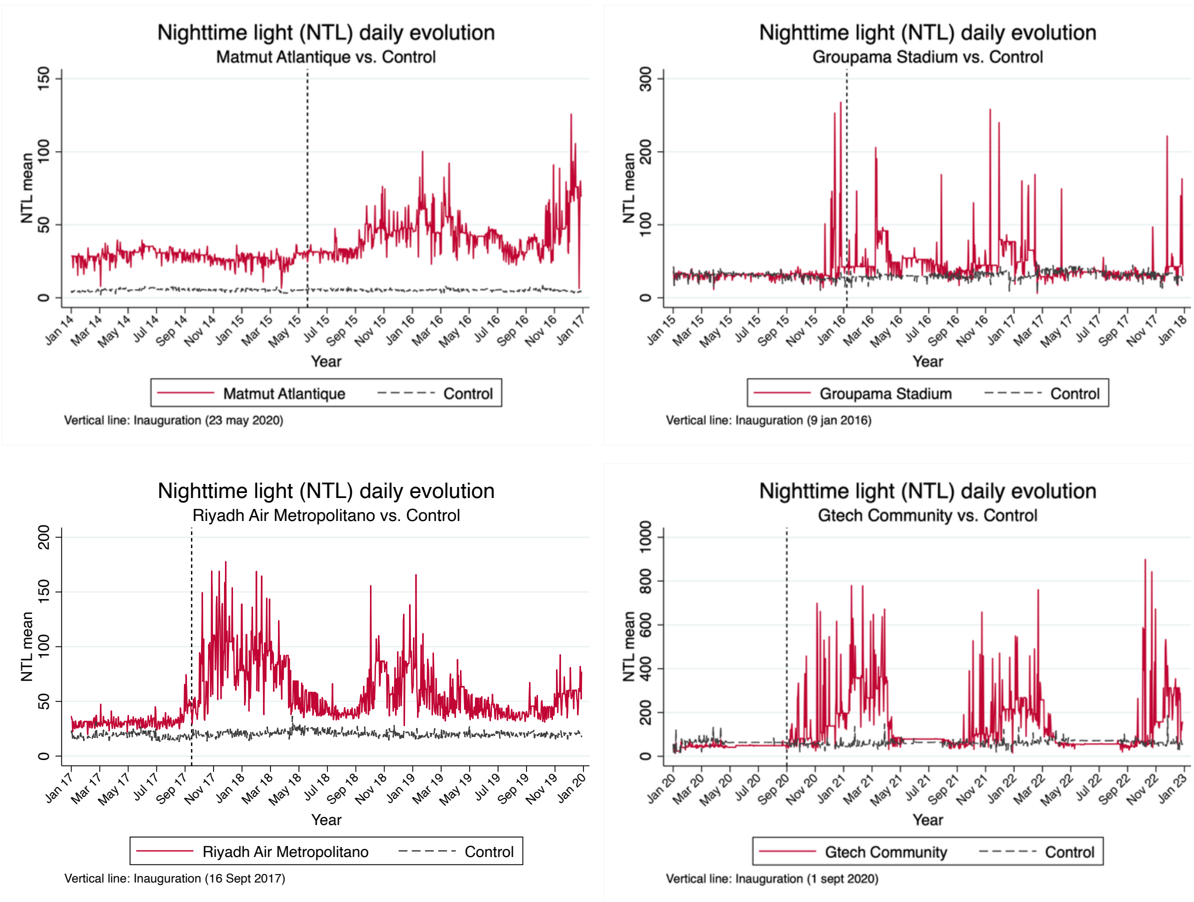

Figure 2. Nighttime light (NTL) daily evolution: Treated vs. Control units.

3. Empirical Strategy

3.1. Spatial Buffers Specification

To assess the spatial decay of stadium effects, we defined multi-tiered influence zones based on proximity to the stadium’s geographic coordinates. Rather than using fixed-distance buffers, we constructed four nested groups of census tracts by selecting the k closest administrative units to each facility. This approach allowed us to isolate direct socioeconomic externalities and identify the spatial decay of activity, moving from the stadium's immediate vicinity to broader urban zones.

A significant methodological challenge arose when implementing spatial boundaries across international datasets. First, there was substantial heterogeneity in the baseline geographic extent of census units across countries. For instance, the IRIS section housing the Matmut Atlantique stadium in Bordeaux spanned 9.6 km², whereas the LSOA containing the Gtech Community Stadium in London spanned 0.6 km². Consequently, defining uniform buffers based on fixed physical distances would have yielded incomparable units of analysis, as a one-kilometer radius might have sat entirely within a single French unit while intersecting multiple British ones. Second, defining spatial units by fixed physical radii resulted in highly heterogeneous sample sizes, distorting the balance between treated and control units across countries. To resolve this asymmetry, we established a standardized number of adjacent administrative units surrounding both the treated stadium coordinates and the centroids of the matched control units: 5, 10, 15, and 30 contiguous neighbors. Table 3 reports the surface area (in km^2) of the treatment and control units, and Figure 3 provides a detailed spatial representation of the treated areas, their respective control units, and the defined buffers.

Table 3. Spatial Buffer Structure and Sample Distribution of Administrative Units (in km^2).

Stadium	Stadium section	Buffer 5	Buffer 10	Buffer 15	Buffer 30
Matmut Atlantique	9.61 km^2	28.58	47.01	51.32	62.24
Control	10.94 km^2	73.08	102.73	151.47	261.37
Groupama Stadium	1.68 km^2	6.09	11.72	15.17	47.24
Control	1.51 km^2	12.68	30.22	50.60	101.23
Riyadh Air Metropolitano	7.69 km^2	8.21	8.82	9.35	10.95
Control	8.27 km^2	8.69	8.84	9.02	15.46
Gtech Community	0.58 km^2	2.29	3.64	4.65	9.64
Control	0.12 km^2	0.83	1.65	2.30	4.16

Alternative buffer specifications are possible. As a robustness check, we calculate the minimum distance from the stadium coordinates to the centroid of the nearest administrative unit, and from a control section’s centroid to that of its nearest neighbor. Subsequently, the radii for the first, second, and third buffers are defined as this minimum distance plus an additive threshold of 1, 2, and 3 km for Groupama; 2, 3, and 4 km for Matmut Atlantique; and 0.5, 1, and 1.5 km for Gtech Community Stadium and Riyadh Air, respectively. Uniform radial extensions are not feasible due to the stark cross-country variation in administrative unit sizes. Consequently, these thresholds have been calibrated on a case-by-case basis to ensure that each buffer encompasses at least one contiguous unit, while preventing spatial overlap between treated and control units. Furthermore, the number of contiguous units analyzed varies across cases to maintain methodological consistency within these local constraints. Table A1 in the

Appendix summarizes the number of areas and the surface area (km^2) for each buffer across stadiums. In the Appendix, Figure A1 presents the evolution of the monthly NTL mean in the first buffer for each case, and Figure A2 illustrates the maps for these alternative buffers.

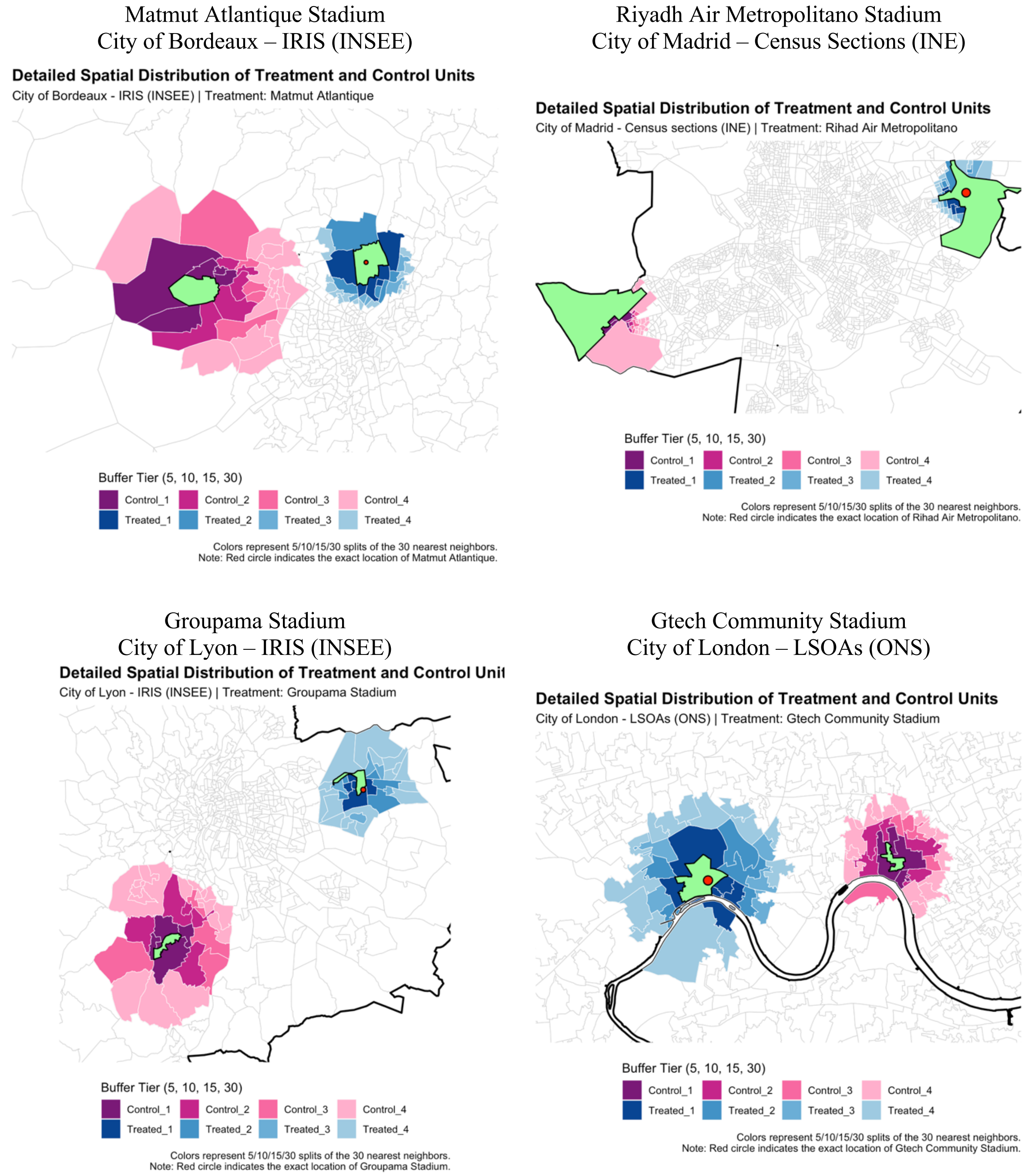

Figure 3. Detailed Spatial Distribution of Treatment and Control Units and Buffers.

3.2. Econometric Framework: Difference-in-Differences (DiD)

To evaluate the localized impacts of each stadium's construction, our empirical strategy relied on separate, independent estimates for each stadium. We used a Difference-in-Differences (DiD) methodology at two distinct levels of temporal and spatial granularity. Additionally, the methodology included two distinct phases of analytical depth. The first phase used a medium-term monthly panel dataset to capture more permanent structural changes, and the second phase exploited a short-term, high-frequency daily panel dataset to capture additional dynamics. To handle high-dimensional fixed effects (census tract and time), we employ the reghdfe estimator (Correia, 2016).

3.2.1. Monthly analysis of nighttime light (NTL) DiD

For the medium-term monthly analysis, we used a Two-Way Fixed Effects (TWFE) model to control for time-invariant unobserved heterogeneity at the census unit level alongside period-specific shocks. Standard errors were robustly clustered at the census unit level (CUSEC, IRIS, and LSOA administrative units in Spain, France, and England, respectively). This specification accounts for spatially correlated error structures, acknowledging that contiguous spatial units within the same district share unobserved localized macroeconomic and political shocks.

This monthly panel dataset covered the period from 2014, incorporating at least one year of pre-inauguration data, to 2025. To isolate these structural trends across our predefined spatial gradients, we estimated the baseline monthly parameters via TWFE linear regressions across distinct buffer zones as follows:

$$\ln\_\mathrm{NTL\_mean}_{it} = \alpha + \gamma_i + \lambda_t + \beta_1 \cdot (\mathrm{Treated}_i \cdot \mathrm{Post}_t) + \varepsilon_{it} \qquad (1)$$

Where the dependent variable is the *log-transformed NTL mean*[6] for census unit i in month t. The term γ_i represents census unit fixed effects, which capture all time-invariant localized characteristics such as baseline geographic density, historical infrastructure, and initial urbanization. The term λ_t represents time fixed effects (months), which control for macroeconomic shocks, seasonal variations in nightlight radiance, and country-wide temporal

[6] We employ the log-plus-one transformation, defined as $\ln(\mathrm{NTL\_mean} + 1)$, to handle zero-value observations in the nighttime light data. This standard procedure effectively addresses the non-negative nature of NTL readings while mitigating the right-skewness of the distribution, thereby facilitating the interpretation of our estimates in relative terms and improving the normality of the regression residuals.

trends. The interaction term $\text{Treated}_\text{i} \cdot \text{Post}_\text{t}$ represents the DiD_{it} estimator. The parameter of interest, β_1, captures the permanent structural shift in NTL induced by the infrastructure shock. ε_{it} is the error term.

To complement the baseline analysis, we employ the event-study framework proposed by Callaway and Sant'Anna (2021). Since our estimations are conducted independently for each stadium, with treatment timing fixed within each sub-sample, we only used this framework to implement an event-study design. This approach allows us to examine pre-treatment trends and estimate the dynamic causal effects of the infrastructure shock on NTL. The group-time average treatment effect $\text{ATT}(\text{g}, \text{t})$ for the single treatment cohort g (the month of that stadium's inauguration) at the calendar period t is defined as:

$$\text{ATT}(\text{g}, \text{t}) = \mathbb{E}[Y_{it}(g) - Y_{it}(0) | G_g = 1] \tag{2}$$

Where $Y_{it}(g)$ represents the potential NTL realized by census unit i at time t under treatment initiated at time g, $(G_g = 1)$, and $Y_{it}(0)$ denotes the counterfactual potential outcome extracted from our matched spatial buffers that remain untreated $(G_g = 0)$. While our baseline TWFE model captures aggregate structural shifts, this framework enables a more granular analysis of the treatment's temporal dynamics. We map the causal impact trajectory from 12 months prior to 36 months after the inauguration, examining pre-treatment coefficients to empirically validate the parallel trends assumption.[7] Finally, we aggregate these estimates to summarize the overall Average Treatment Effect on the Treated (ATT).

3.2.2. Daily analysis of nighttime light (NTL) DiD

For the short-term daily analysis, we set the temporal window to a panel spanning 12 months prior to 36 months after the inauguration. This setup sought to determine whether the localized luminosity observed post-inauguration was driven by transient radiance on event days, such as football league matches or cup competitions, or by a permanent structural shift in baseline NTL. Specifically, by including event-day indicators, this high-frequency model isolated the

[7] The inauguration date is defined as the date of the first match held at the stadium. However, the data reflect potential anticipation effects, as construction activities often precede the official opening. This is evident in the case of the Groupama Stadium and, to a lesser extent, the Riyadh Air Metropolitano, where NTL intensity trends begin to shift prior to the inaugural match, as illustrated by the high-frequency daily data in Figure 2.

residual baseline impact, verifying whether the infrastructural intervention yielded a sustained externality in the surrounding areas independently of match-day activity. We conducted two alternative specifications. The first incorporated an event-day dummy variable to isolate the immediate impact of match-day operations on NTL. The second used match attendance to account for event size. Note that during the COVID-19 pandemic, attendance was strictly restricted to zero in several instances, affecting attendance during the 2020-2021 season.

To identify the stadium's impact on NTL, we estimated a TWFE-augmented model that accounted for event-day occurrences and match attendance. The empirical model is defined as follows:

$$\begin{aligned}\mathrm{ln\_ntl\_mean}_{\mathrm{it}} = \alpha + \gamma_{\mathrm{i}} + \delta_{\mathrm{m}} + \beta_1(\mathrm{Treated}_{\mathrm{i}} \cdot \mathrm{Post}_{\mathrm{t}}) + \beta_2(\mathrm{Event}_{\mathrm{it}}) \\ + \beta_3(\mathrm{Treated}_{\mathrm{i}} \cdot \mathrm{Post}_{\mathrm{t}} \cdot \mathrm{Event}_{\mathrm{it}}) + \varepsilon_{\mathrm{it}}\end{aligned} \quad (3)$$

Where the dependent variable is the *log-transformed NTL mean* for census unit *i* on day *t*. The DiD Estimator $\beta_1(\mathrm{Treated}_i \cdot \mathrm{Post}_t)$ captures the structural change in baseline NTL in treated sections relative to control sections following the stadium inauguration, excluding the potential effect of event days. $\beta_2(\mathrm{Event}_{it})$ represents the direct effect of match-day operations, measured either as a binary indicator or as *log-transformed attendance (ln_att)*, which controls for systemic variations in NTL on match days. The interaction term $\beta_3(\mathrm{Treated}_i \cdot \mathrm{Post}_t \cdot \mathrm{Event}_{it})$ captures the heterogeneous treatment effect conditional on an event. This parameter indicates how the infrastructure shock (DiD effect) modifies NTL levels on event days, providing insight into the stadium-induced mitigation or saturation effects. The term γ_i represents census unit fixed effects. Given the daily panel structure, we omit calendar-day fixed effects to avoid perfect multicollinearity; instead, we incorporate month-of-the-year fixed effects (δ_m) to control for temporal confounding and seasonality. For all estimations, standard errors are clustered at the census-unit level.

4. Results

4.1. Monthly NTL Results

Table 4 reports the DiD TWFE regression results over the 2014-2025 period.[8] We consider buffers containing the 5, 10, 15, and 30 nearest sections to both the treatment and control areas to assess the sensitivity of our findings to spatial definition. Table 4 also distinguishes between two sets of estimates: columns 1-4 include the specific census unit where the stadium is located, and columns 5-8 exclude this central unit to isolate the impact on the surrounding area.

As the dependent variable is the *log-transformed NTL mean*, the coefficients β represent semi-elasticities. To facilitate economic interpretation, we transform these estimates into percentage changes using the expression $(\exp(\beta) - 1) \times 100$. The results show a substantial increase in NTL in the immediate vicinity of the new stadiums. As shown in Table 4 column (1), the Gtech Community Stadium and Groupama Stadium exhibit a statistically significant increase of approximately 48.9% and 49.6%, respectively, in average NTL intensity compared to the control group. This upward trend is consistently observed across the other stadiums: the Matmut Atlantique shows a 69.2% increase, and the Riyadh Air Metropolitano shows a 66.7% increase. These findings provide evidence that constructing large sports stadiums is associated with increased local economic activity, as proxied by NTL data.

Table 4 also reveals a consistent positive impact of stadium inaugurations on local NTL mean across all cases, but with a clear spatial decay pattern: the estimated coefficients systematically decrease as the buffer size expands. This decay is particularly pronounced in stadiums located in urban areas (Groupama, Riyadh Air, and Gtech), where the infrastructure's economic externality is more localized and dissipates rapidly with increasing distance from the core. Conversely, the Matmut Atlantique exhibits a more persistent impact across spatial buffers, likely reflecting its location within an industrial zone where the baseline NTL is more sensitive to large-scale structural changes. The results are robust to the inclusion or exclusion of the stadium's census unit. For the Matmut Atlantique, excluding the stadium's census tract does not significantly alter the findings, as the impacts remain broadly similar to those observed when it is included.

[8] The analysis starts in 2014, providing a two-year temporal buffer after the 2012 matching baseline to ensure robust identification and avoid cross-contamination of NTL trends.

Table 4. TWFE DiD Results - Spatial Decay Analysis (monthly).

	Including Stadium Section				Excluding Stadium Section			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Buffer size	Top 5	Top 10	Top 15	Top 30	Top 5	Top 10	Top 15	Top 30
Matmut Atlantique								
DiD	0.526^{**}	0.519^{***}	0.430^{***}	0.385^{***}	0.564^{**}	0.537^{***}	0.437^{***}	0.386^{***}
	(0.176)	(0.123)	(0.114)	(0.081)	(0.198)	(0.130)	(0.120)	(0.083)
Within R^2	0.096	0.095	0.068	0.050	0.117	0.106	0.072	0.051
Groupama Stadium								
DiD	0.403^{***}	0.340^{***}	0.297^{***}	0.259^{***}	0.374^{**}	0.319^{***}	0.281^{***}	0.250^{***}
	(0.116)	(0.083)	(0.063)	(0.037)	(0.132)	(0.087)	(0.064)	(0.037)
Within R^2	0.058	0.055	0.050	0.050	0.052	0.053	0.048	0.050
Riyadh Air Metropolitano								
DiD	0.511^{***}	0.368^{***}	0.296^{***}	0.175^{***}	0.495^{***}	0.346^{***}	0.277^{***}	0.161^{***}
	(0.097)	(0.091)	(0.074)	(0.050)	(0.108)	(0.090)	(0.071)	(0.046)
Within R^2	0.143	0.092	0.072	0.037	0.130	0.083	0.065	0.033
Gtech Community								
DiD	0.398^{***}	0.234^{***}	0.141^{**}	0.064^{*}	0.339^{***}	0.188^{***}	0.104^{*}	0.043
	(0.089)	(0.070)	(0.058)	(0.036)	(0.084)	(0.062)	(0.051)	(0.032)
Within R^2	0.105	0.044	0.018	0.005	0.088	0.033	0.012	0.002
Observations	1728	3168	4608	8928	1440	2880	4320	8640

Note: Standard errors in parentheses clustered at the census unit level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is ln(NTL mean+1). Column headers denote the spatial buffer size (number of neighboring sections).

Table A2 in the Appendix replicates the main specification across alternative buffer distances and demonstrates a high degree of consistency with Table 4. This alternative specification allows for a spatial interpretation of the radiance spillover. As we expand the distance from the stadium, we observe a marked spatial decay. At the Riyadh Air Metropolitano and Gtech Community stadiums, increasing the buffer by 0.5 km leads to radiance declines of approximately 14.8% and 47.1%, respectively (columns 1 and 2). Similarly, the Matmut Atlantique and Groupama Stadium show radiance declines of 11.6% and 18.7%, respectively, across the 1 km spatial increase. This rapid yet heterogeneous attenuation underscores the localized nature of the stadium's economic impact, which remains highly concentrated in the immediate periphery of the infrastructure.

Although our results indicate that stadium construction is associated with increased local economic activity, the underlying mechanisms remain difficult to identify precisely. In the case of Madrid, where data availability permits a more granular analysis, we show in Appendix Table A3 that increases in NTL are positively correlated with the expansion of local hospitality services, suggesting that changes in this sector may be one channel contributing to the observed increase in luminosity.

4.1.1. Monthly NTL Results: Event Study

We implement a dynamic event-study analysis to trace the trajectory of causal impacts over time and complement the regression results by capturing how the stadium's economic impact intensifies or stabilizes in the months following its opening. Figure 4 graphically presents the estimated coefficients and their respective 95% confidence intervals. For this graphical analysis, we adopt the Top 10-section buffer (including the stadium's unit) as an intermediate spatial solution that balances local intensity with broader effects. While the estimation uses the full available sample, the graphical presentation is based on a window spanning the 12 months prior to and 36 months following the stadium's inauguration, thereby highlighting changes in NTL intensity around the treatment date. Given that the event-study plots provide a comprehensive visual representation of the dynamic effects, we omit the tabulation of individual unit coefficients for brevity; instead, we report the aggregated ATT for all post-inauguration periods below each graph.

Although the estimates obtained from the TWFE model and the Doubly Robust Inverse Probability Weighting (DRIPW) estimator of Callaway and Sant'Anna (2021) differ slightly, the results remain remarkably consistent, reinforcing the robustness of our findings. The dynamic analysis yields an ATT of 0.525 for the Gtech Community Stadium, closely aligning with the 0.519 estimated for the Matmut Atlantique. In percentage terms, these coefficients correspond to an average increase in NTL intensity of approximately 69.1% and 68.0%, respectively. Regarding the remaining stadiums, the estimated coefficients range from 0.154 to 0.177, implying an average NTL growth between 16.7% and 19.4%. The sign and significance levels remain consistent, but the magnitudes are slightly more conservative compared to the baseline specifications, where coefficients ranged from 0.234 to 0.368 (translating to a 26.4% to 44.5% increase in light intensity) (Table 4, Column 2). Our results confirm a sustained positive impact on local activity post-inauguration. However, rather than a singular, linear impact, the effect exhibits substantial month-to-month variation. A notable exception is the Matmut Atlantique, which shows a consistent, sustained increase in NTL and appears largely impervious to the seasonal fluctuations observed in the other case studies.

Regarding the parallel trends assumption, the results collectively support the validity across all countries. Interestingly, for the Riyadh Air Metropolitano, the t-1 period is statistically significant, suggesting a potential anticipation effect prior to the inauguration; however, the average pre-trend coefficient remains statistically non-significant (0.0005, p=0.656). For the

Matmut Atlantique, none of the six pre-inauguration periods differ statistically from zero, and the overall pre-trend test confirms its non-significance (0.002, p=0.505). Similarly, at the Gtech Community and Groupama Stadium, although we observe minor significance in three sporadic periods, the aggregate pre-trend estimates remain statistically indistinguishable from zero (0.001, p=0.220 and 0.0005, p=0.829, respectively).

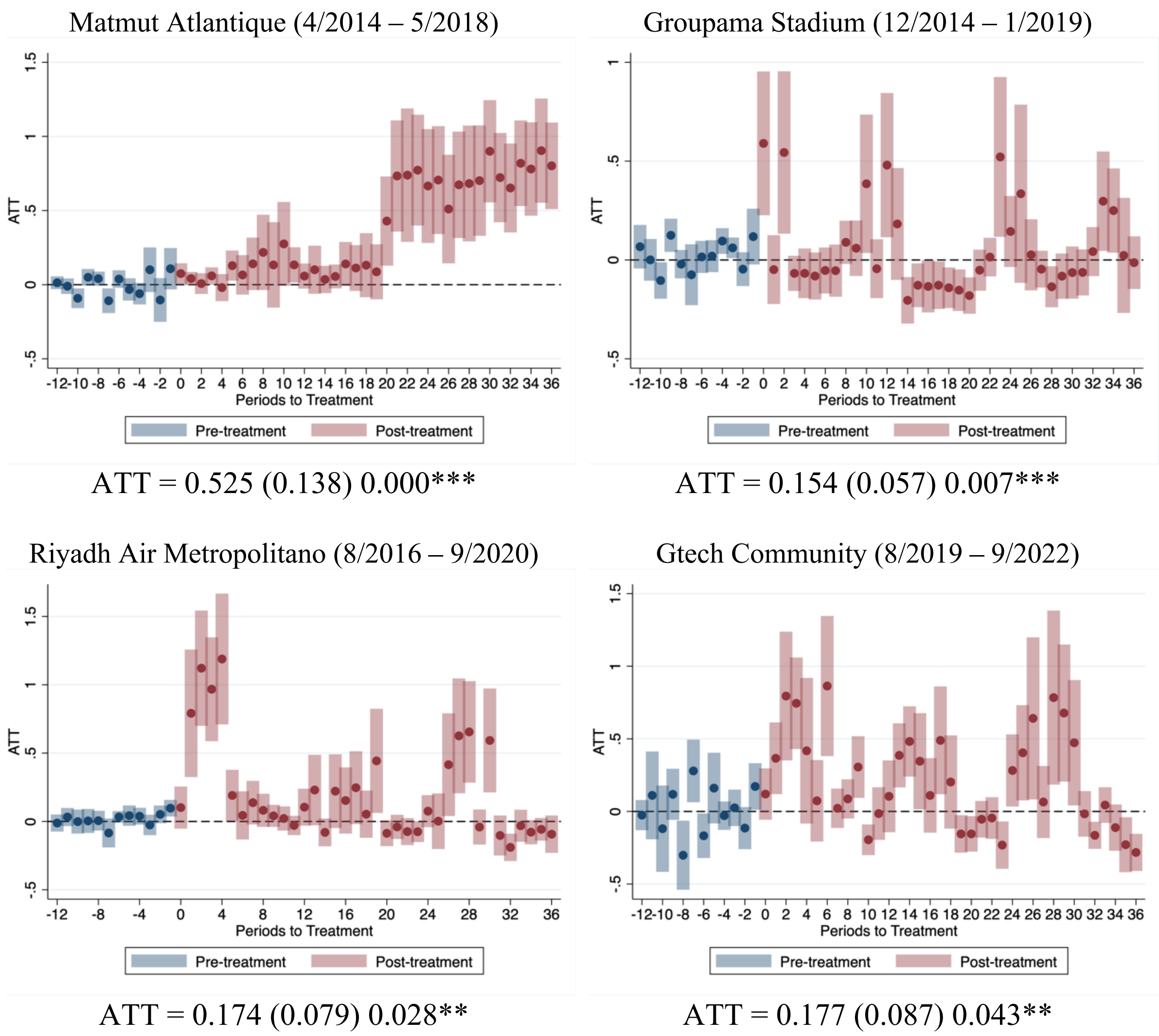

Figure 4. Event Study Trends and Post-Inauguration Average Treatment Effects (ATT).

4.2. Daily NTL Results: DiD augmented

This section presents daily-level results derived from Equation (3), which examines the determinants of the daily NTL mean. This analysis disentangles whether the observed transitory NTL increase is mainly driven by shocks associated with event-day activity or by other activity types. Table 5 reports the main findings using *log-transformed match attendance* (*ln_att*) to measure intensity, and Table A5 in the Appendix uses an alternative binary indicator, *Match day*. This dual specification isolates the effect of audience volume from the systemic luminosity fluctuations occurring on match days. Descriptive statistics of stadiums' attendance figures are in Appendix Table A4.

Table 5 shows a highly consistent pattern across all four stadiums, showing three key patterns. First, the DiD coefficient, representing the structural change in NTL baseline following the stadium's inauguration, is consistently positive and highly significant across all specifications and stadium sites. Notably, estimates that include the stadium's census unit consistently yield higher impact magnitudes than those that exclude it. This result is consistent with the monthly pattern and confirms that the stadium-related infrastructure acts as a catalyst for localized economic activity. The radiance intensity peaks within the immediate stadium vicinity and exhibits a clear spatial decay, as evidenced by the varying buffer sizes.

Second, the *log-transformed attendance* (*ln_att*) variable captures the impact of match-day attendance on NTL intensity within the control group—that is, the systemic radiance response to event-day activity independent of the structural stadium effect. In most cases (Matmut Atlantique, Gtech Community, and Groupama Stadium), this coefficient is largely non-significant or weakly positive, suggesting that fluctuations in attendance do not generate broad, systemic increases in NTL across the study area in the absence of the stadium's structural influence. In sharp contrast, the Riyadh Air Metropolitano exhibits a consistently negative and significant effect. Finally, the DiD * *log-transformed attendance* (*ln_att*) interaction term—our primary measure of the synergy between infrastructure and attendance—captures the marginal radiance spillover from match attendance, conditional on the stadium being operational. The consistently negative sign of this coefficient across all sites suggests a spatial displacement of economic activity.

To test the robustness of our results, we replicate the analysis using a binary indicator for event days (*Match day*) instead of *log-transformed attendance* (see Table A5 in the Appendix). The results demonstrate a high degree of structural consistency; the DiD coefficients remain stable, significant, and positive across all specifications, confirming that the permanent radiance uplift is independent of how we model event-day.

Furthermore, the DiD * *Match day* interaction term retains its negative sign and statistical significance across most stadium sites, confirming that the radiance-damping effect is a robust phenomenon. When transitioning to this binary dummy, we observe a slight attenuation in statistical precision and magnitude, particularly in the Groupama and Matmut Atlantique sites.

Table 5. TWFE DiD Results controlling for stadium attendance (daily).

	Including Stadium Section				Excluding Stadium Section			
Buffer	Top 5	Top 10	Top 15	Top 30	Top 5	Top 10	Top 15	Top 30
Matmut Atlantique								
DiD	0.254**	0.279***	0.237***	0.237***	0.197**	0.251***	0.218***	0.227***
	(0.086)	(0.061)	(0.057)	(0.048)	(0.069)	(0.055)	(0.054)	(0.047)
ln_att	0.001	0.002*	0.002**	0.000	0.002	0.002**	0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
DiD*lnatt	-0.004**	-0.004***	-0.003***	-0.001	-0.004**	-0.004***	-0.003***	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R2-Within	0.057	0.068	0.051	0.051	0.037	0.057	0.044	0.047
Obs.	17.532	32.142	46.752	90.582	16.071	30.681	45.291	89.121
Groupama Stadium								
DiD	0.173**	0.175***	0.170***	0.131***	0.153*	0.163***	0.160***	0.125***
	(0.073)	(0.054)	(0.039)	(0.023)	(0.084)	(0.056)	(0.039)	(0.023)
ln_att	-0.000	-0.001	-0.001	-0.001*	0.000	-0.001	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
DiD*lnatt	-0.004*	-0.002	-0.001	-0.000	-0.003	-0.002	-0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R2-Within	0.026	0.035	0.039	0.029	0.022	0.032	0.037	0.028
Obs.	13.152	24.112	35.072	67.952	12.056	23.016	33.976	66.856
Riyadh Air Metropolitano								
DiD	0.485***	0.347***	0.272***	0.152***	0.481***	0.328***	0.253***	0.138***
	(0.050)	(0.068)	(0.059)	(0.039)	(0.058)	(0.072)	(0.060)	(0.038)
ln_att	-0.005**	-0.003***	-0.002***	-0.001*	-0.005**	-0.003**	-0.002**	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
DiD*lnatt	-0.007**	-0.004*	-0.003*	-0.002**	-0.008*	-0.004*	-0.002	-0.002**
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
R2-Within	0.098	0.062	0.043	0.020	0.092	0.055	0.038	0.017
Obs.	13.140	24.090	35.040	67.890	12.045	22.995	33.945	66.795
Gtech Community								
DiD	0.557***	0.308***	0.209**	0.097**	0.487***	0.248**	0.163**	0.071*
	(0.105)	(0.106)	(0.081)	(0.047)	(0.098)	(0.097)	(0.072)	(0.041)
ln_att	0.003	0.002	0.002*	0.001**	0.003	0.002	0.002*	0.001**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
DiD*lnatt	-0.017***	-0.012***	-0.010***	-0.007***	-0.016***	-0.011***	-0.009***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
R2-Within	0.087	0.037	0.021	0.007	0.080	0.029	0.016	0.004
Obs.	12.960	23.760	34.560	66.960	11.880	22.680	33.480	65.880

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Dependent variable is ln (NTL mean +1). We construct the attendance variable as ln (attendance + 1) to account for the presence of zero-attendance periods.

To further ensure that these findings are not driven by extreme luminosity outliers or reporting anomalies, we perform an additional sensitivity analysis, excluding days exceeding the 90th percentile of NTL intensity in the stadium census unit (approximately 100 observations per stadium, see Table A6 in the Appendix), showing consistency of the core estimates' sign and magnitude. Finally, Table A7 in the Appendix presents an alternative specification that uses a weekend dummy variable (capturing Friday and Saturday nights) to account for spikes in commercial activity. In the Groupama and Riyadh Air Metropolitano cases, we generally observe a positive weekend effect; however, the interaction term is negative, consistent with our match-day analysis. Conversely, for the Matmut Atlantique, the interaction term is positive, suggesting that the stadium area exhibits higher luminosity during weekends relative to the control units. A similar, albeit nuanced, pattern is found for the Gtech Community Stadium. These heterogeneous results across venues highlight that, while stadiums generally increase local nighttime activity, the timing and intensity of these effects may be shaped by the surrounding local land-use context and the degree to which the stadium is integrated into the urban areas.

5. Discussion and concluding remarks

The construction of new sports stadiums is frequently justified on the grounds of local economic development, yet the empirical evidence supporting this claim remains limited. This paper contributes to the literature by providing new evidence from four newly constructed stadiums in Western and Southern Europe, using high-frequency, high-resolution nighttime light (NTL) data. We include a temporal disaggregation (monthly and daily output) that has not previously been applied in this context.

Our results are consistent across all four cases. The monthly analysis shows positive and statistically significant increases in local NTL intensity following the stadium inauguration, with a clear spatial decay as distance from the venue increases. This pattern is consistent with the rapid attenuation of agglomeration externalities documented in the urban economics literature (Rosenthal & Strange, 2020) and with prior evidence on the localized nature of stadium-induced activity (Abbiasov & Sedov, 2023; Lindlacher & Pirich, 2025; Funahashi & Cardazzi, 2026). Regarding luminosity, Pfeifer et al. (2018) document short-run gains in luminosity near sports venues but more durable effects only from accompanying transportation investments. Our findings have implications for understanding which economic areas have benefited most from these luminosity gains. As expected, the TWFE DiD results show that estimates including the stadium's census unit consistently yield larger magnitudes than those excluding it. However, the observed local economic activation is highly robust to the inclusion or exclusion of the stadium's census unit. This is a relevant finding, as it means that the gains in luminosity cannot be explained by the new stadium infrastructure alone. In the extreme case of the Matmut Atlantique, the observed impact is even slightly higher when excluding the stadium's own census unit. This is, however, a singular case, as the stadium was built in an industrial site, where upgraded logistics, improved infrastructure, and peripheral businesses in the neighboring stadium's census units may be easier to develop than in other, more central and residential units.

Regarding the magnitude of the results, based on the ATT coefficients from the Callaway & Sant'Anna (2021) event study, the implied NTL increases range from approximately 17% to 19% for three stadiums, with Matmut Atlantique as a notable outlier at around 69%, likely reflecting its atypically low baseline luminosity as an industrial area. Previous research has translated these increases in luminosity into GDP gains (Beyer et al., 2022). However, this translation has been estimated only for emerging markets and developing economies, and its applicability to high-income European contexts has not yet been established. If we take the most conservative estimate, the Groupama Stadium (ATT = 0.154, implying approximately a 17% increase in local NTL intensity), and apply the elasticity between NTL and GDP established by Beyer et al. (2022), we would obtain an implied local GDP gain of approximately 11% in the immediate vicinity of the stadium. However, this translation should be interpreted with much caution and is presented here only as an illustrative benchmark.

More importantly for our research questions, the event study analysis reveals pronounced episodic spikes in luminosity rather than a sustained structural shift; a pattern of periodicity overlooked in the existing literature. This represents a novel contribution, as NTL data clearly suggest that stadiums generate intermittent local activation rather than broad urban regeneration, a distinction that studies relying on aggregated annual measures cannot observe. Our daily analysis further advances this literature and might offer a natural explanation: the luminosity spikes observed in the monthly data are simply driven by match-day activity. However, our results do not support this interpretation. The DiD effect remains positive and significant after controlling for event days and match attendance, suggesting that the increase in NTL following the inauguration reflects a baseline change in local nighttime activity not driven by sporting events. If anything, the negative and significant interaction between the DiD estimator and match attendance points in the opposite direction, indicating that event days are associated with a relative reduction in surrounding luminosity. We interpret this finding cautiously, as a working hypothesis. One possibility is that the operational demands of large events temporarily displace commercial activity in adjacent areas, consistent with evidence of spatial displacement documented elsewhere (Matheson, 2019; Stitzel & Rogers, 2019). While data limitations prevent direct identification of the underlying mechanisms, additional evidence from the analysis conducted in Madrid suggests that the expansion of the hospitality sector may be one channel through which stadium construction contributes to localized increases in urban activity.

Additionally, the event study design provides valuable insights by allowing us to trace the temporal evolution of the effects rather than summarizing them as a single post-inauguration average. This is particularly informative for the Matmut Atlantique, where NTL intensity increased progressively rather than immediately following inauguration. The stadium opened in May 2015, with the mission of hosting UEFA Euro 2016 matches. The gradual increase we observe suggests that economic returns may depend on subsequent investment in complementary infrastructure and programs. Public policy evaluations should emphasize the use of these tools when interested in specific complementary programs and investments.

This study has several limitations. First, our sample comprises only four stadiums, which limits generalizability despite the consistency of results across cases. Second, while we control for sporting events, we lack systematic data on non-sporting uses of the venues, such as concerts, cultural events, and other gatherings, which may account for a share of the luminosity spikes we observe. Third, NTL is an indirect proxy for economic activity subject to well-documented measurement challenges, including blurring and cross-satellite comparability issues (Ch et al., 2021); variables such as employment, business counts, or local revenue remain the most precise indicators of the mechanisms at play but are not available at the temporal and spatial resolution required by this research question. Fourth, the sensitivity of results to buffer specification, while partially addressed through robustness checks, remains a methodological choice and a challenge given the cross-national heterogeneity in administrative unit sizes. Finally, translating NTL changes into economic magnitudes remains constrained by the lack of an elasticity estimate calibrated to high-income countries using VIIRS data, a gap that future research may seek to address. Establishing a reliable NTL-to-GDP elasticity for high-income economies would also enable more precise quantification of the local economic footprint of large sport-related infrastructure investments while accounting for key spatial and temporal nuances.

Taken together, the results suggest that stadiums function as multi-purpose urban nodes that generate intermittent local activity rather than sustained economic renewal. This distinction has direct relevance for public policy. The case for large public subsidies to stadium construction has long rested on claims of structural economic transformation (Bradbury et al., 2024; Moore, 2024), claims that our findings do not support. At the same time, the localized and episodic effects we document are not trivial, and their magnitude likely depends on the surrounding land-use context in ways that deserve further attention.

Data availability statement

The code and data supporting the findings of this study will be made publicly available on Harvard Dataverse (https://doi.org/10.7910/DVN/XL7YGH) upon publication. Nighttime light data are not redistributed here due to source licensing but are freely available from NASA's Earthdata platform (Black Marble product suite) following individual registration. The socioeconomic data used in this study were obtained from the relevant national statistical offices (e.g., INE for Spain, INSEE for France, and ONS for the United Kingdom).

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Appendix

Table A1. Spatial Buffer Structure and Sample Distribution of Administrative Units (in kms).

Stadium	Stadium section	Minimum distance	First buffer	Second buffer	Third buffer
Matmut Atlantique			**2 km**	**3 km**	**4 km**
Treated area (in km^2)	9.61 km^2	0.28 km	13.24	45.91	55.94
Number of sections			*1*	*9*	*24*
Control area (in km^2)	10.94 km^2	2.21 km	95.99	101.45	116.67
Number of sections			*7*	*9*	*14*
Groupama Stadium			**1km**	**2 km**	**3 km**
Treated area (in km^2)	1.68 km^2	0.64 km	6.88	18.72	37.49
Number of sections			*7*	*17*	*28*
Control area (in km^2)	1.51 km^2	0.59 km	11.21	17.52	34.68
Number of sections			*4*	*6*	*11*
Riyadh Air Metropolitano			**0.5km**	**1km**	**1.5km**
Treated area (in km^2)	7.69 km^2	0.79 km	9.64	12.22	15.75
Number of sections			*19*	*46*	*71*
Control area (in km^2)	8.27 km^2	1.23 km	8.51	8.84	15.16
Number of sections			*3*	*10*	*25*
Gtech Community			**0.5km**	**1km**	**1.5km**
Treated area (in km^2)	0.58 km^2	0.19 km	0.89	4.04	8.92
Number of sections			*2*	*12*	*27*
Control area (in km^2)	0.12 km^2	0.25 km	1.65	4.16	8.76
Number of sections			*10*	*30*	*65*

Notes: In the Gtech Community Stadium case study, although areas and minimum distances are small, expanding the spatial buffer is restricted by proximity constraints; since the selected units are in close proximity, further enlargement would induce overlapping zones and severe spatial spillover contamination. Conversely, the Matmut Atlantique case presents the opposite challenge: a 1 km buffer initial threshold yields no valid administrative sections, necessitating a larger initial buffer to capture sufficient control units. The number of total administrative sections in each buffer is indicated in italics.

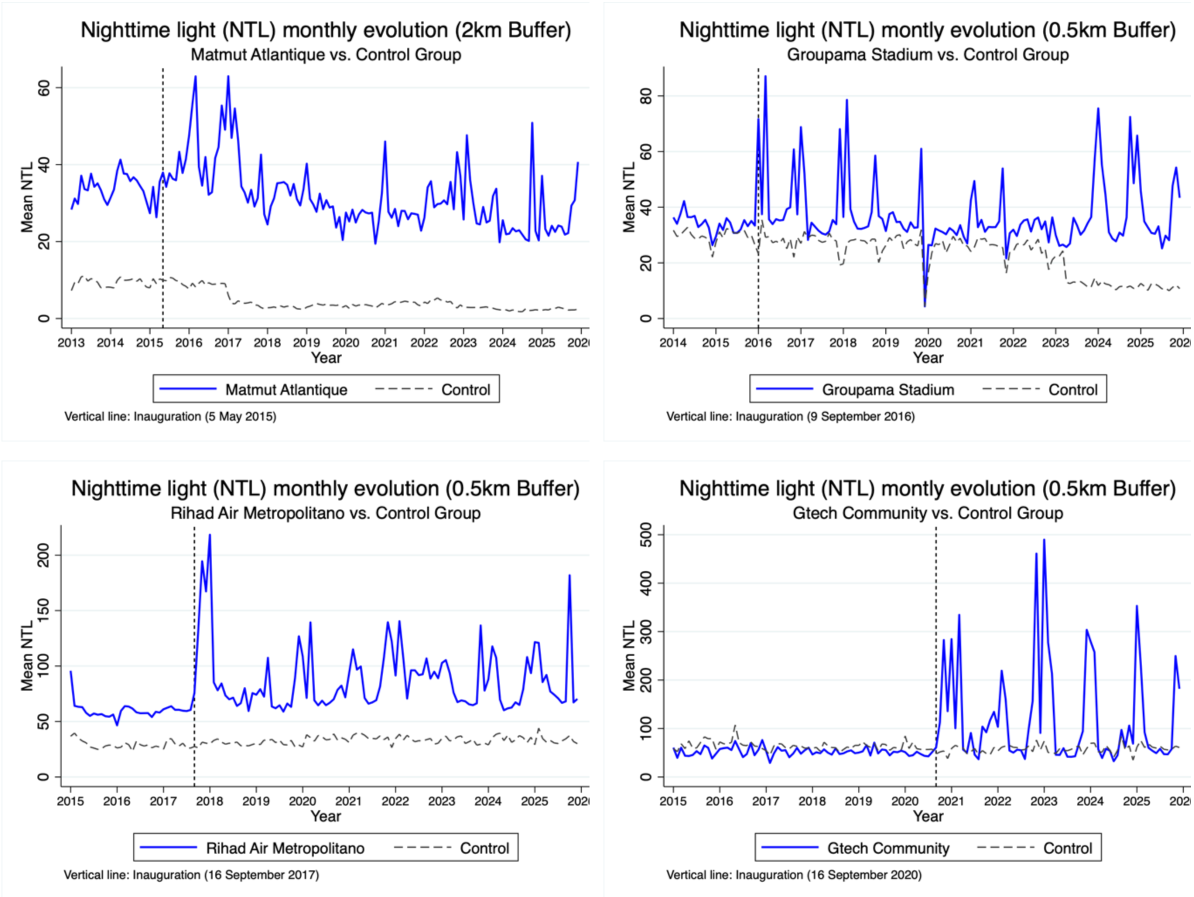

Figure A1. Nighttime light (NTL) monthly evolution: Treated vs. Control buffers.

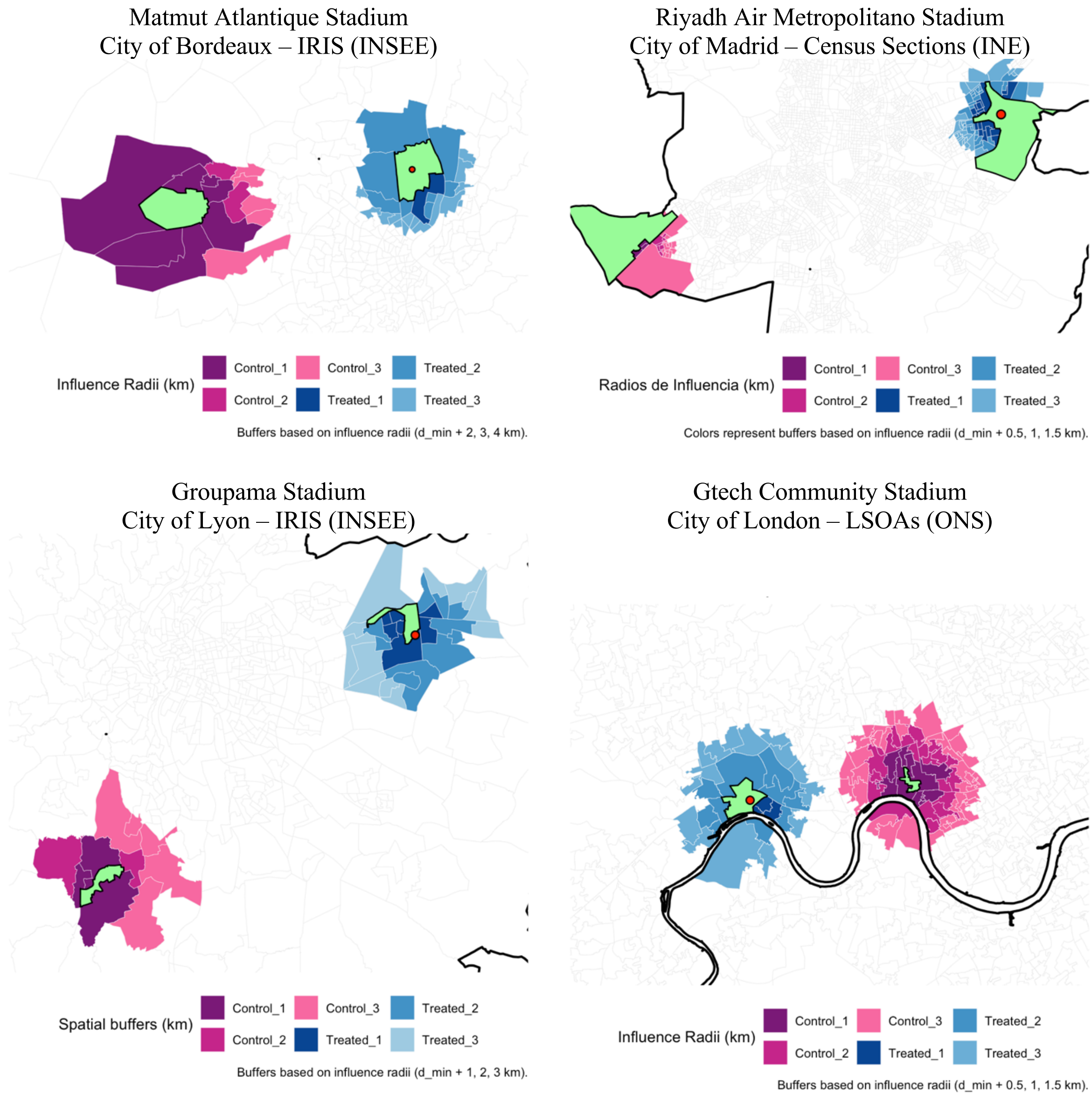

Figure A2. Detailed Spatial Distribution of Treatment and Control Units and Buffers.

Table A2. TWFE DiD Results - Spatial Decay Analysis (monthly).

	Including Stadium Section			Excluding Stadium Section		
	(1) Buffer 1	(2) Buffer 2	(3) Buffer 3	(5) Buffer 1	(6) Buffer 2	(7) Buffer 3
Matmut Atlantique (2013-2025)						
DiD	0.522***	0.460***	0.431***	0.489**	0.473***	0.444***
	(0.150)	(0.124)	(0.119)	(0.158)	(0.133)	(0.125)
Within R^2	0.078	0.115	0.093	0.050	0.126	0.100
Observations	1.560	3.120	6.240	1.248	2.808	5.928
Groupama Stadium (2014-2025)						
DiD	0.383***	0.318***	0.288***	0.369***	0.311***	0.281***
	(0.099)	(0.058)	(0.055)	(0.106)	(0.061)	(0.058)
Within R^2	0.052	0.044	0.048	0.049	0.043	0.049
Observations	1.872	3.600	5.904	1.584	3.312	5.616
Riyadh Air Metropolitano (2014-2025)						
DiD	0.160**	0.067*	0.055**	0.133**	0.059*	0.050**
	(0.062)	(0.037)	(0.026)	(0.061)	(0.035)	(0.025)
Within R^2	0.009	0.003	0.004	0.005	0.002	0.003
Observations	3.168	7.656	12.936	2.904	7.392	12.672
Gtech Community (2014-2025)						
DiD	0.639***	0.167**	0.088**	0.571***	0.118	0.063
	(0.070)	(0.083)	(0.044)	(0.063)	(0.075)	(0.038)
Within R^2	0.209	0.022	0.008	0.178	0.012	0.004
Observations	1.848	5.808	12.408	1.584	5.544	12.144

Standard errors in parentheses clustered at DCOMIRIS/Census Section/LSOA11CD level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Note: Dependent variable is ln(NTL+1). Column headers denote the spatial buffer size (1, 2, 3km radii for the Groupama Stadium; 2, 3, and 4km radii for the Matmut Atlantique, and 0.5, 1, and 1.5km radii for the Riyadh Air Metropolitano and Gtech Community).

Validation of NTL as a Proxy for Local Economic Activity

While our results indicate that stadium construction is associated with higher levels of NTL, identifying the exact underlying mechanisms remains challenging. To provide an additional validation of our main outcome variable, we leverage monthly establishment-level data from the Madrid City Council and examine whether changes in NTL intensity are associated with observed human economic activity.

Specifically, we estimate a two-way fixed effects (TWFE) relating NTL intensity to the number of establishments in Food and Beverage Services (CNAE-2009, National Classification of Economic Activities, the official Spanish standard aligned with the European NACE classification, number 56), a sector likely to be sensitive to changes in NTL activity. Based on 281,420 observations (mean 8.6; SD 10.4), Table A3 shows a positive and statistically significant relationship between the two variables. These results provide additional support for the use of NTL as a proxy for localized economic activity.

Table A3. Impact of the number of establishments on NTL 2015-2025.

	(1)
Number of establishments	0.002^{**}
	(0.001)
Observations	281.429
Within R^2	0.001

Note: Dependent variables are CNAE2009 56. Note that the following months are excluded from our estimations due to data gaps in the raw administrative registry: 2015m7, 2017m12, 2022m4, 2025m1, and 2025m2. Standard errors in parentheses, clustered at CUSEC level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4. Summary statistics of match-day attendance by stadium.

Stadium	Obs	Mean	Std. dev.	Min	Max
Matmut Atlantique	68	25227.01	13560.77	715	89000
Groupama Stadium	64	39691.11	14702.72	3841	57841
Riyadh Air Metropolitano	81	46592.01	20772.42	1764	67942
Gtech Stadium	85	8689.41	7310.03	0	17137
Gtech Without COVID-19	60	12310.00	5545.66	1000	17137

Note: The analysis for the Gtech Community Stadium excludes 15 matches played behind closed doors due to COVID-19 restrictions, reducing the effective sample from 85 to 60 matches.

Table A5. TWFE DiD Results controlling for match day (daily NTL data).

	Including Stadium Section				Excluding Stadium Section			
	Top 5	Top 10	Top 15	Top 30	Top 5	Top 10	Top 15	Top 30
Matmut Atlantique								
DiD	0.254**	0.280***	0.237***	0.237***	0.197**	0.252***	0.218***	0.227***
	(0.086)	(0.061)	(0.057)	(0.048)	(0.069)	(0.055)	(0.054)	(0.047)
Match day	0.014	0.019**	0.019***	0.004	0.019	0.021**	0.021***	0.005
	(0.011)	(0.009)	(0.006)	(0.004)	(0.011)	(0.008)	(0.006)	(0.004)
DiD x match	-0.037**	-0.040***	-0.035***	-0.010	-0.040**	-0.042***	-0.036***	-0.010
	(0.016)	(0.013)	(0.010)	(0.007)	(0.017)	(0.013)	(0.010)	(0.007)
Within R^2	0.057	0.068	0.051	0.051	0.037	0.057	0.044	0.047
Obs	17.532	32.142	46.752	90.582	16.071	30.681	45.291	89.121
Groupama Stadium								
DiD	0.173**	0.175***	0.170***	0.131***	0.153*	0.163***	0.160***	0.125***
	(0.073)	(0.054)	(0.039)	(0.023)	(0.084)	(0.056)	(0.039)	(0.023)
Match day	0.002	-0.006	-0.002	-0.006	0.005	-0.004	-0.001	-0.005
	(0.009)	(0.007)	(0.005)	(0.004)	(0.009)	(0.007)	(0.005)	(0.004)
DiD x match	-0.043**	-0.020	-0.013	-0.002	-0.037*	-0.016	-0.010	-0.000
	(0.018)	(0.012)	(0.009)	(0.006)	(0.020)	(0.012)	(0.009)	(0.006)
Within R^2	0.026	0.035	0.039	0.029	0.022	0.032	0.037	0.028
Obs	13.152	24.112	35.072	67.952	12.056	23.016	33.976	66.856
Riyadh Air Metropolitano								
DiD	0.485***	0.347***	0.272***	0.151***	0.481***	0.328***	0.253***	0.138***
	(0.050)	(0.068)	(0.059)	(0.039)	(0.058)	(0.072)	(0.060)	(0.038)
Match day	-0.053**	-0.036***	-0.027***	-0.010*	-0.046**	-0.032**	-0.023**	-0.008
	(0.020)	(0.012)	(0.009)	(0.005)	(0.020)	(0.012)	(0.009)	(0.005)
DiD x match	-0.076**	-0.042*	-0.026	-0.018**	-0.079**	-0.040*	-0.023	-0.016*
	(0.029)	(0.020)	(0.016)	(0.009)	(0.035)	(0.022)	(0.016)	(0.009)
Within R^2	0.098	0.062	0.043	0.020	0.091	0.055	0.038	0.017
Obs	13.140	24.090	35.040	67.890	12.045	22.995	33.945	66.795
Gtech Community								
DiD	0.552***	0.305***	0.207**	0.096**	0.484***	0.246**	0.162**	0.070*
	(0.104)	(0.105)	(0.081)	(0.047)	(0.097)	(0.096)	(0.071)	(0.040)
Match day	-0.020	-0.014	-0.005	0.001	-0.011	-0.009	-0.002	0.003
	(0.015)	(0.010)	(0.007)	(0.004)	(0.013)	(0.008)	(0.006)	(0.004)
DiD x match	-0.053**	-0.040***	-0.036***	-0.027***	-0.062***	-0.044***	-0.038***	-0.028***
	(0.017)	(0.012)	(0.009)	(0.006)	(0.017)	(0.012)	(0.010)	(0.006)
Within R^2	0.086	0.036	0.020	0.006	0.079	0.029	0.015	0.004
Obs	12.960	23.760	34.560	66.960	11.880	22.680	33.480	65.880

Table A6. TWFE DiD Results controlling for match day excluding >90% NTL days.

	Including Stadium Section				Excluding Stadium Section			
	Top 5	Top 10	Top 15	Top 30	Top 5	Top 10	Top 15	Top 30
Matmut Atlantique (number of excluded days >90% NTL mean = 139)								
DiD	0.238**	0.271***	0.231***	0.233***	0.238**	0.271***	0.231***	0.233***
	(0.078)	(0.058)	(0.055)	(0.048)	(0.078)	(0.058)	(0.055)	(0.048)
Match day	0.018	0.020**	0.020***	0.005	0.018	0.020**	0.020***	0.005
	(0.011)	(0.008)	(0.006)	(0.004)	(0.011)	(0.008)	(0.006)	(0.004)
DiD x match	-0.032*	-0.038***	-0.033***	-0.009	-0.032*	-0.038***	-0.033***	-0.009
	(0.018)	(0.013)	(0.010)	(0.007)	(0.018)	(0.013)	(0.010)	(0.007)
Within R^2	0.053	0.066	0.050	0.050	0.053	0.066	0.050	0.050
Obs	17.393	32.003	46.613	90.443	17.393	32.003	46.613	90.443
Groupama Stadium (number of excluded days >90% NTL mean = 109)								
DiD	0.161**	0.169***	0.165***	0.129***	0.153*	0.163***	0.160***	0.125***
	(0.072)	(0.053)	(0.038)	(0.023)	(0.084)	(0.056)	(0.039)	(0.023)
Match day	0.005	-0.004	-0.001	-0.006	0.005	-0.004	-0.001	-0.005
	(0.009)	(0.007)	(0.005)	(0.004)	(0.009)	(0.007)	(0.005)	(0.004)
DiD x match	-0.036*	-0.016	-0.011	-0.000	-0.037*	-0.016	-0.010	-0.000
	(0.018)	(0.012)	(0.009)	(0.005)	(0.020)	(0.012)	(0.009)	(0.006)
Within R^2	0.025	0.035	0.039	0.029	0.022	0.032	0.037	0.028
Obs	13.043	24.003	34.963	67.843	12.056	23.016	33.976	66.856
Riyadh Air Metropolitano (number of excluded days >90% NTL mean = 104)								
DiD	0.474***	0.339***	0.266***	0.148***	0.481***	0.328***	0.253***	0.138***
	(0.050)	(0.067)	(0.058)	(0.038)	(0.058)	(0.072)	(0.060)	(0.038)
Match day	-0.051**	-0.035***	-0.026***	-0.010*	-0.046**	-0.032**	-0.023**	-0.008
	(0.020)	(0.012)	(0.009)	(0.005)	(0.020)	(0.012)	(0.009)	(0.005)
DiD x match	-0.071**	-0.039*	-0.023	-0.016*	-0.079**	-0.040*	-0.023	-0.016*
	(0.030)	(0.021)	(0.016)	(0.009)	(0.035)	(0.022)	(0.016)	(0.009)
Within R^2	0.095	0.060	0.042	0.019	0.091	0.055	0.038	0.017
Obs	13.036	23.986	34.936	67.786	12.045	22.995	33.945	66.795
Gtech Community (number of excluded days >90% NTL mean = 96)								
DiD	0.522***	0.288***	0.195**	0.089**	0.484***	0.246**	0.162**	0.070*
	(0.089)	(0.097)	(0.075)	(0.044)	(0.097)	(0.096)	(0.071)	(0.040)
Match day	-0.016	-0.012	-0.003	0.002	-0.011	-0.009	-0.002	0.003
	(0.013)	(0.009)	(0.007)	(0.004)	(0.013)	(0.008)	(0.006)	(0.004)
DiD x match	-0.043	-0.034**	-0.032***	-0.025***	-0.062***	-0.044***	-0.038***	-0.028***
	(0.024)	(0.015)	(0.011)	(0.007)	(0.017)	(0.012)	(0.010)	(0.006)
Within R^2	0.086	0.036	0.020	0.006	0.079	0.029	0.015	0.004
Obs	12.864	23.664	34.464	66.864	11.880	22.680	33.480	65.880

Table A7. TWFE DiD Results controlling for weekends (daily NTL data).

	Including Stadium Section				Excluding Stadium Section			
	Top 5	Top 10	Top 15	Top 30	Top 5	Top 10	Top 15	Top 30
Matmut Atlantique								
DiD	0.249^{**}	0.274^{***}	0.232^{***}	0.233^{***}	0.192^{**}	0.246^{***}	0.213^{***}	0.223^{***}
	(0.086)	(0.060)	(0.057)	(0.048)	(0.068)	(0.054)	(0.054)	(0.047)
Weekend	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.009^{***}	-0.011^{***}	-0.010^{***}	-0.010^{***}	-0.009^{***}
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
DiD x weekend	0.009^{***}	0.008^{***}	0.010^{***}	0.011^{***}	0.008^{**}	0.008^{***}	0.009^{***}	0.011^{***}
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Within R^2	0.057	0.068	0.051	0.051	0.037	0.057	0.044	0.048
Obs	17.532	32.142	46.752	90.582	16.071	30.681	45.291	89.121
Groupama Stadium								
DiD	0.172^{**}	0.175^{***}	0.170^{***}	0.131^{***}	0.153^{*}	0.163^{***}	0.161^{***}	0.125^{***}
	(0.072)	(0.054)	(0.039)	(0.023)	(0.083)	(0.056)	(0.039)	(0.023)
Weekend	0.008^{*}	0.007^{**}	0.005^{**}	0.002	0.007	0.006^{**}	0.005^{**}	0.002
	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)
DiD x weekend	-0.010	-0.007^{*}	-0.005^{*}	-0.000	-0.010	-0.006^{*}	-0.005^{*}	0.000
	(0.006)	(0.003)	(0.003)	(0.002)	(0.006)	(0.004)	(0.003)	(0.002)
Within R^2	0.026	0.034	0.038	0.029	0.022	0.032	0.037	0.028
Obs	13.152	24.112	35.072	67.952	12.056	23.016	33.976	66.856
Riyadh Air Metropolitano								
DiD	0.487^{***}	0.350^{***}	0.274^{***}	0.154^{***}	0.483^{***}	0.332^{***}	0.256^{***}	0.141^{***}
	(0.051)	(0.069)	(0.060)	(0.039)	(0.059)	(0.072)	(0.061)	(0.038)
Weekend	-0.004	0.001	0.002	0.007^{***}	-0.003	0.001	0.003	0.007^{***}
	(0.006)	(0.003)	(0.002)	(0.002)	(0.006)	(0.003)	(0.002)	(0.002)
DiD x weekend	-0.037^{**}	-0.030^{***}	-0.020^{**}	-0.016^{***}	-0.037^{**}	-0.028^{**}	-0.018^{*}	-0.015^{***}
	(0.013)	(0.010)	(0.009)	(0.005)	(0.015)	(0.010)	(0.009)	(0.005)
Within R^2	0.093	0.060	0.042	0.019	0.088	0.054	0.037	0.016
Obs	13.140	24.090	35.040	67.890	12.045	22.995	33.945	66.795
Gtech Community								
DiD	0.546^{***}	0.298^{**}	0.200^{**}	0.089^{*}	0.477^{***}	0.239^{**}	0.154^{**}	0.063
	(0.104)	(0.105)	(0.081)	(0.047)	(0.097)	(0.096)	(0.071)	(0.040)
Weekend	0.001	-0.003	-0.002	-0.002	0.002	-0.003	-0.002	-0.002
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
DiD x weekend	0.001	0.009^{**}	0.011^{***}	0.011^{***}	-0.001	0.009^{*}	0.011^{***}	0.011^{***}
	(0.005)	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)
Within R^2	0.084	0.035	0.020	0.006	0.077	0.027	0.014	0.003
Obs	12.960	23.760	34.560	66.960	11.880	22.680	33.480	65.880