

Measuring Regional Economic Development from the Ground Up: Gas Station Infrastructure as an Alternative to Nighttime Lights

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Abstract

Accurate and timely measurement of economic development at the subnational level remains challenging, particularly where official regional statistics are released with substantial delays or are available only at coarse spatial scales. This paper introduces the Gas Station Index (GSI), a novel bottom-up indicator of regional economic development constructed from open-source geospatial data on approximately 100,000 gas stations and their surrounding built environments across 207 regions in 18 countries spanning Europe, East Asia, South America, and Africa. The index combines information on gas-station service quality, the density and diversity of nearby amenities within 200 m and 200–500 m, and local accessibility, thereby capturing spatial variation in infrastructure, consumption opportunities, and economic activity. Empirically, the GSI is strongly associated with regional GDP per capita and achieves an R^2 of approximately 0.75, comparable to the predictive performance of satellite-based nighttime lights. At the same time, the two indicators capture partly distinct dimensions of local economic development: whereas nighttime lights reflect economic activity observed from above, the GSI provides complementary information on ground-level infrastructure and consumption environments. These findings demonstrate the potential of readily available geospatial data to improve the timely measurement of regional development and spatial inequalities, particularly where conventional regional statistics are limited or delayed.

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JEL Classification: C43 , E01 , O18 , R11 , R12

1 Introduction

Accurate and timely measurement of economic development at the subnational level remains a persistent challenge in regional research. Gross domestic product (GDP)

is the standard measure of economic activity, but regional GDP statistics are often released with substantial delays, reported unevenly across countries, or available only for relatively broad geographic areas. These limitations matter especially for analysing spatial inequalities, regional convergence, and local economic dynamics, where timely, geographically detailed information is essential. To address these shortcomings, researchers have increasingly relied on alternative indicators of economic activity. Earlier contributions used consumption-based measures such as electricity use (e.g., [International Monetary Fund 2006](#)). [Young \(2012\)](#) similarly constructed consumption-based proxies for developing countries using household survey data.

More recently, the increasing availability of remotely sensed data has substantially expanded the possibilities for measuring economic activity at fine spatial scales. Satellite-derived nighttime lights have become one of the most widely used alternative indicators of economic development following the contributions of [Sutton et al. \(2007\)](#) and [Henderson et al. \(2012\)](#). Subsequent research has demonstrated their usefulness for measuring economic activity across countries and regions and for studying spatial development where conventional statistics are limited (e.g., [Keola et al. 2015](#); [Pinkovskiy and Sala-i Martin 2016](#); [Henderson et al. 2018](#); [Bargain et al. 2025](#)). At the same time, nighttime lights do not fully represent local economic conditions. Temporal comparisons can be difficult, saturation can limit usefulness in highly illuminated areas, and sensitivity can be limited in rural or low-intensity environments ([Gibson et al. 2020](#)). More fundamentally, nighttime lights observe economic activity from above and therefore primarily capture those dimensions of development that generate visible luminosity.

The growing availability of geolocated digital information creates a complementary opportunity: measuring regional development from the ground up. A growing literature has examined infrastructure-based and digital indicators such as bank branches and ATMs, firm networks, web-based interactions, and coworking spaces as signals of local economic activity and entrepreneurial dynamism ([Kireyeva et al. 2021](#); [Abbasiharofteh et al. 2023](#); [Benmelech et al. 2023](#); [Mariotti et al. 2021](#); [Gauger et al. 2021](#); [Clifton et al. 2022](#)). Yet relatively little attention has been paid to whether a ubiquitous form of consumer-facing infrastructure can provide a systematic indicator of regional economic development across countries. This paper explores that possibility using gas station infrastructure.

The rationale for using gas station infrastructure as an indicator of regional economic development is threefold. First, the density and distribution of gas stations reflect mobility and fuel demand, which are closely related to income, commuting patterns, vehicle use, and access to services; greater mobility and vehicle usage generally accompany higher levels of economic activity and living standards. Second, because fuel retailing typically operates on relatively thin margins, stations tend to be strategically located where sufficient and sustained demand exists, including economically active urban centres, market towns, and major transport corridors. [Zhu et al. \(2024\)](#) show that gas-station location decisions depend on factors such as population density, road connectivity, and fuel demand, linking station networks to underlying patterns of economic activity. Third, sustaining a viable gas-station network requires a sufficiently large consumer base and purchasing power, reflected not only in fuel demand and

travel but also in the viability of complementary services such as convenience stores, cafés, and other on-site amenities. Taken together, these features make gas-station infrastructure a manifestation of private investment, consumer demand, mobility, and commercial development, and therefore a potentially informative indicator of regional economic development.

This intuition is consistent with several strands of economic theory. Models of urban and regional development emphasise households’ and firms’ tendency to cluster around infrastructure nodes that improve access to markets and services (Fujita et al. 1999; Glaeser 2008). Infrastructure is both a determinant and a signal of productivity and economic development (Calderón and Servén 2004), while mobility and travel demand tend to increase with income and economic activity (Goodwin et al. 2004). Structural transformation also shifts household expenditure toward services and more diversified forms of consumption as incomes rise (Herrendorf et al. 2014). Together, these mechanisms provide a theoretical basis for expecting gas-station infrastructure and its surrounding service environment to vary systematically with regional development.

As an initial illustration of this idea, Figure 1 compares two regions that differ substantially in geography, development level, and continental setting. Tokyo Prefecture in Japan, one of the highest-income regions in the sample, with GDP per capita in purchasing-power terms of EUR 81,853 in 2021, is characterised by a dense and highly developed gas-station network. By contrast, the Southwestern Region of North Macedonia, with GDP per capita of EUR 20,101 in purchasing-power terms in 2021, displays a substantially sparser infrastructure pattern. This comparison is intended only to illustrate the underlying intuition; whether such differences systematically reflect regional economic development is an empirical question examined across the full sample.

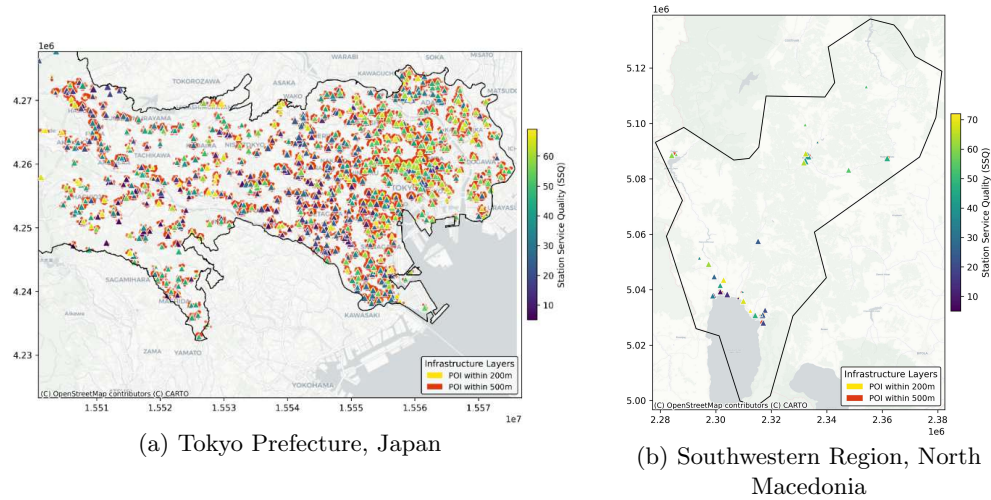


Fig. 1 A tale of gas station infrastructure in two contrasting regions.

To operationalise this idea, we introduce the **Gas Station Index (GSI)**, a novel bottom-up indicator of regional economic development constructed from open-source and crowd-sourced geospatial data. Rather than relying simply on the number or density of gas stations, the GSI combines information on station-level service characteristics, the density and diversity of nearby amenities, and measures of spatial accessibility. In this way, it captures not only the physical presence of infrastructure but also the broader consumer-facing environment surrounding it. The index is designed to be transparent, scalable, and relatively inexpensive to construct across countries and regions.

We apply the GSI to approximately 100,000 geolocated gas stations across 207 regions in 18 countries spanning Europe, East Asia, South America, and Africa. The empirical analysis shows that the index is strongly associated with regional GDP per capita, explaining approximately 75% of its cross-regional variation in our preferred specifications. Its predictive performance is comparable to that of satellite-based nighttime lights. Importantly, however, the two indicators appear to capture partly distinct dimensions of regional economic activity. Nighttime lights primarily reflect luminosity generated by economic activity, whereas the GSI contains information related to mobility, accessibility, private infrastructure investment, and the surrounding service economy. The results therefore suggest that the two measures are complementary rather than simply competing proxies.

The paper makes three main contributions. First, it introduces a new measure of regional economic development based on a single but information-rich form of consumer-facing infrastructure. The contribution lies not in counting gas stations alone, but in combining their service characteristics, surrounding amenity environment, and accessibility into a unified regional indicator. Second, the paper provides a multi-country empirical assessment of the relationship between the GSI and regional GDP per capita and directly compares its explanatory power with that of nighttime lights. The results show that ground-level infrastructure data can provide predictive information comparable to established remote-sensing indicators while capturing partly non-overlapping dimensions of economic activity. Third, the paper demonstrates how the GSI can be used to study spatial heterogeneity in infrastructure–development relationships. Spatial patterns and regional typologies reveal development corridors, infrastructure-rich peripheral regions, metropolitan areas with high infrastructure saturation, and high-output regions whose economic activity is not fully reflected in consumer-facing infrastructure. More broadly, the analysis contributes to regional science by showing how granular ground-level geospatial data can complement conventional regional statistics in identifying spatial disparities and heterogeneous development patterns within countries.

The remainder of the paper is organised as follows. Section 2 presents the conceptual framework and construction of the Gas Station Index. Section 3 provides an empirical application of the GSI, describing the data, data-processing procedures, and regional sample. Section 4 evaluates the relationship between the GSI and regional GDP per capita and compares its explanatory performance with that of nighttime lights. Section 5 examines spatial patterns and develops regional typologies based on the relationship between infrastructure and economic outcomes. Section 6 concludes

by summarising the main findings, discussing the study’s broader implications and limitations, and outlining directions for future research.

2 Construction of the Gas Station Index

We construct the Gas Station Index (GSI) around five pillars: Station Service Quality (SSQ), Amenity Density within 200 metres (AD200), Amenity Variety within 200 metres (AV200), Amenity Variety within 200–500 metres (AV500), and Gas Station Accessibility (GSA). Together, these pillars capture complementary dimensions of gas-station infrastructure and its surrounding service environment. The first four pillars are constructed at the individual station level and subsequently aggregated to the regional level, while Gas Station Accessibility is calculated directly at the regional level.

2.1 Station Service Quality

The Station Service Quality (SSQ) pillar captures the level of services, investment, and functionality of each gas station. It combines information on six characteristics: brand tier, fuel availability, opening hours, payment options, on-site retail services, and metadata completeness. These elements are aggregated into a score ranging from 0 to 100, with higher values indicating higher service standards and a broader range of services.

Because the availability and completeness of station-level information vary across countries and regions, we apply two fallback mechanisms to reduce the risk of systematically undervaluing stations in data-sparse areas. First, where some service information is missing, the score is partially imputed using the station’s brand tier. Second, stations with very low observed SSQ scores (below 10) but above-average amenity density or diversity are assigned a baseline score of 30. This adjustment reflects the assumption that stations located in economically active environments are likely to provide at least a minimum level of service even when detailed station-level information is incomplete.

2.2 Amenity Density within 200 metres

The Amenity Density pillar (AD200) captures the intensity of economic activity in a gas station’s immediate surroundings. For each station, we identify all relevant Points of Interest (POIs) within a 200-metre radius through a spatial query using a pre-filtered bounding box, followed by an exact-distance calculation based on the Haversine formula.

The POIs included in the construction of the GSI comprise restaurants, supermarkets, cafés, bars, car-repair facilities, hotels, pharmacies, fast-food outlets, convenience stores, banks, charging stations, ATMs, bus stations, and parking facilities. Each POI is assigned a weight according to its type, reflecting its relative contribution to the surrounding service environment. For example, a restaurant receives a weight of 1.0, while a fast-food outlet receives a weight of 0.6.

For station (i), amenity density is calculated as:

$$AD200_i = \ln \left(1 + \frac{\sum_{j \in POIs} w_j}{\pi(0.2)^2} \right) \quad (1)$$

where w_j denotes the weight assigned to POI (j), and (0.2) corresponds to a radius of 0.2 kilometres.

Economic activity around gas stations is typically highly skewed: a station in a dense metropolitan area may have hundreds of nearby amenities, whereas a rural station may have only a few. The logarithmic transformation therefore reduces the influence of extremely dense urban locations and prevents them from disproportionately determining regional scores. Accordingly, AD200 captures the intensity of the weighted service environment surrounding each station while allowing for diminishing marginal differences at very high amenity densities.

2.3 Amenity Variety within 200 metres and 200–500 metres

Amenity Variety captures the diversity and functional complexity of the economic activities surrounding each gas station. Two measures are constructed: **AV200**, which captures amenity diversity within the immediate 200-metre radius, and **AV500**, which captures diversity in the wider 200–500-metre surrounding area.

Whereas AD200 measures the intensity of nearby economic activity, the amenity-variety indicators capture how widely this activity is distributed across service types. Greater diversity is interpreted as reflecting a more complex and developed local service environment.

Amenity variety is measured using weighted Shannon entropy:

$$AV_{r,i} = \ln \left(1 - \sum_{k=1}^K p_k \ln(p_k) \right) \quad (2)$$

where r denotes the relevant spatial buffer (200 or 500 meters), k indexes amenity categories, and p_k represents the share of the weighted count of amenity type in the total weighted number of amenities within the corresponding area.

A higher entropy value indicates that amenities are distributed more evenly across more functional categories and therefore reflects greater service diversity. AV200 captures economic heterogeneity in the station's immediate surroundings, while AV500 captures the complexity of the broader local environment. The latter is particularly relevant for rural and transit-oriented stations, where commercial activities may be located somewhat farther from the station itself.

As with amenity density, the resulting entropy measure is logarithmically transformed. This transformation reduces the influence of observations with exceptionally high functional diversity and allows the indicator to capture differences in the order of magnitude of local service complexity.

2.4 Gas Station Accessibility

Gas Station Accessibility (GSA) differs from the preceding four pillars because it is calculated directly at the regional rather than station level. The indicator combines

two complementary measures of gas-station availability: the number of stations relative to population and the number of stations relative to land area.

Specifically, GSA combines the number of gas stations per 10,000 inhabitants with the number of gas stations per 100 km². Both components are logarithmically transformed to reduce the influence of extreme differences in population density and regional size and are then assigned equal weights:

$$\text{GSA}_r = \frac{1}{2} \left[\ln \left(\frac{\text{Stations}_r}{\text{Population}_r/10,000} \right) + \ln \left(\frac{\text{Stations}_r}{\text{Area}_r/100} \right) \right] \quad (3)$$

where Stations_r , Population_r , and Area_r denote the number of gas stations, population, and land area of region (r), respectively.

The two components capture different dimensions of accessibility. Stations per 10,000 inhabitants measure availability relative to potential demand, whereas stations per 100 km² capture the network's spatial density. Combining them reduces the risk that either densely populated but geographically small regions or sparsely populated but geographically large regions dominate the accessibility measure.

2.5 Aggregation to the regional level

The calculation of SSQ, AD200, AV200, and AV500 generates four station-level pillar scores before regional normalization and index construction. For each administrative region, NUTS 2 or NUTS 3, depending on the country, the station-level values of each pillar are averaged to obtain a single raw regional value:

$$P_R = \frac{1}{N_R} \sum_{i=1}^{N_R} P_i \quad (4)$$

where P_i denotes the value of a given pillar for station i , and N_R is the number of gas stations located in region R .

The Station Service Quality pillar is therefore aggregated using the arithmetic mean of station-level scores. For AD200, AV200, and AV500, the logarithmic transformations described in Equations (1) and (2) are applied before aggregation. This log-mean approach reduces the influence of exceptionally dense or diversified station environments on the regional average.

The GSA pillar does not require this aggregation step because it is constructed directly at the regional level.

2.6 Normalization of the regional pillars

Once raw regional values have been obtained for all five pillars, each pillar is normalized across the full sample of regions using a two-step procedure. The first step limits the influence of extreme regional observations through winsorization. For each pillar, regional values are clipped at the 5th and 95th percentiles of the corresponding global distribution:

$$P_r^{\text{clip}} = \min \{ \max (P_r, Q_{0.05}), Q_{0.95} \} \quad (5)$$

where $Q_{0.05}$ and $Q_{0.95}$ denote the 5th and 95th percentiles of the pillar's distribution across all regions. This procedure reduces the influence of extreme observations, such as exceptionally dense metropolitan areas or very sparsely populated regions, without removing them from the sample.

In the second step, the winsorized values are transformed using global min-max normalization:

$$P_r^* = \frac{P_r^{\text{clip}} - \min(P^{\text{clip}})}{\max(P^{\text{clip}}) - \min(P^{\text{clip}})} \quad (6)$$

which rescales each pillar to a common interval between 0 and 1. This makes the five dimensions directly comparable despite differences in their original units and distributions.

2.7 Construction of the composite GSI

The final Gas Station Index is obtained by assigning equal weight to each of the five normalized pillars. For region (R), the GSI is therefore calculated as:

$$\text{GSI}_R = \frac{1}{5} (\text{SSQ}'_R + \text{AD200}'_R + \text{AV200}'_R + \text{AV500}'_R + \text{GSA}'_R) \quad (7)$$

Equal weighting is used to avoid imposing an ex ante assumption that any single dimension of gas-station infrastructure is more important than the others in reflecting regional economic development. The resulting index ranges from 0 to 1, with higher values indicating a stronger combination of station service quality, surrounding economic activity, functional diversity, and accessibility.

3 Empirical Application of the Gas Station Index

This section applies the Gas Station Index (GSI) to a sample of 207 subnational regions across 18 countries spanning four continents. The sample includes European economies (Albania, Austria, Bulgaria, Croatia, Greece, Hungary, Italy, Montenegro, North Macedonia, Romania, Serbia, Slovakia, and Slovenia), East Asian economies (Japan and South Korea), South American economies (Brazil and Chile), and South Africa. In total, the dataset contains approximately 100,000 geolocated gas stations, which are extracted, scored, and aggregated according to the methodology described in Section 2.

3.1 Data Collection and Processing

We initially considered several alternative approaches to data collection. We did not use the Overpass API because it was unstable at this scale, and we excluded the Google Places API because of its cost and limited reproducibility. Instead, the analysis relies on pre-downloaded .osm.pbf files from Geofabrik.de, which provides freely available and regularly updated country-level extracts of OpenStreetMap data ([OpenStreetMap contributors 2025](#)). This approach offers three important advantages for constructing the GSI: scalability, reproducibility, and zero acquisition cost.

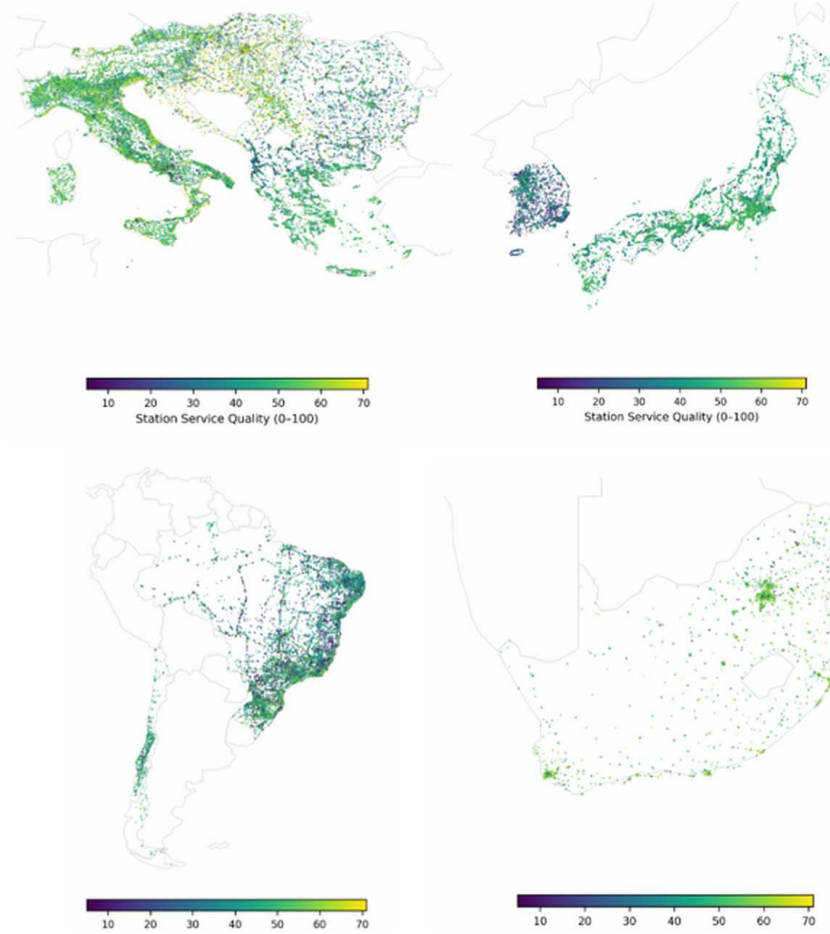


Fig. 2 Spatial distribution of gas stations across Europe, East Asia, South America, and South Africa

The core data used to construct the index are extracted from these .osm.pbf files. Using *osmium*, we identify all gas stations tagged as `amenity=fuel` and retrieve the available station-level attributes, including geographic location, brand, name, presence of a shop, car wash and toilet facilities, payment options, and other service characteristics. In parallel, we extract a curated set of surrounding Points of Interest (POIs), such as restaurants, convenience stores, pharmacies, and hotels, from the same source. These POIs are subsequently used to construct the amenity-density and amenity-variety pillars described in Section 2.

Figure 2 presents the spatial distribution of the gas-station network, with individual stations displayed according to their Station Service Quality (SSQ) scores. The maps reveal substantial variation in both infrastructure density and station-level service quality across continents, countries, and regions. In Europe, dense and interconnected station networks are particularly visible in Italy, Austria, and parts of Central Europe,

while in East Asia high concentrations are observed around major metropolitan areas such as Tokyo and Seoul. These differences illustrate the geographic breadth and heterogeneity of the underlying dataset and provide a first indication of the spatial variation that the GSI is designed to capture.

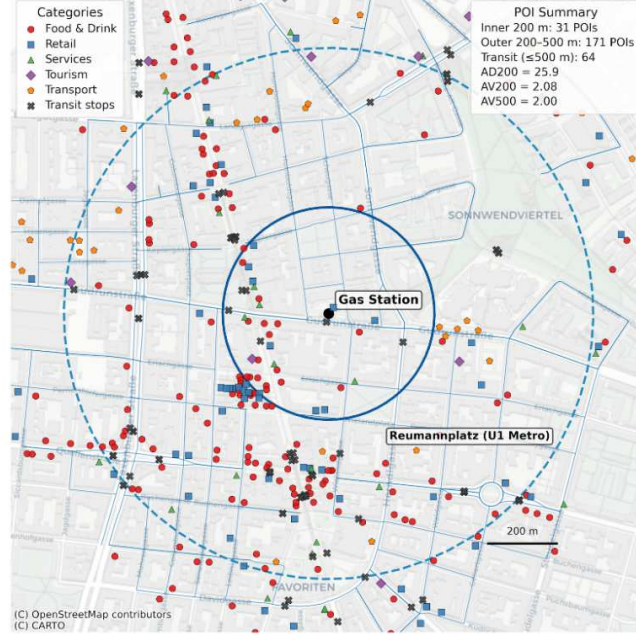


Fig. 3 A gas station in AT13 - Vienna region

To illustrate index construction at the station level, Figure 3 shows a gas station in the AT13 Vienna region in Austria. The selected station records one of the highest station-level scores in the dataset and illustrates how the GSI components are constructed. It is located on a major street in a high-value urban area near Reumannplatz and close to Vienna Central Station. In addition to fuel services, the station includes a market, fast-food facilities, a café, and a car wash. Its immediate surroundings also contain a major boulevard, several bus stops, and a metro station. The location therefore represents a dense urban service environment within Vienna.

Table 1 reports the station-level scores for the relevant pillars. We apply the same procedure to all other gas stations in the AT13 Vienna region. We then average the station-level values of SSQ, AD200, AV200, and AV500 within the region to obtain the corresponding raw regional pillar scores, and we calculate Gas Station Accessibility (GSA) directly at the regional level, as described in Section 2. Finally, the regional pillar scores are normalized across the full sample using the global min-max procedure. The resulting normalized scores for AT13 Vienna are presented in Table 2.

Table 1 Scores of the GSI pillars for an example gas station in Vienna (AT13)

Pillar	Data	Raw value	Logged value (AD & AV)
SSQ	The gas station has an SSQ score of 65/100: 20 points for being a global brand; 11 points for four payment methods; 14 points for four fuel types; 10 points for rich metadata; and 10 points for a kiosk tag.	65/100	–
AD200	The gas station has an AD200 score of 364.46 POI objects in a 200 m radius, signifying an exceptionally economically active area.	358.09	5.88
AV200	The gas station has an AV200 score of 3.51, signifying high Shannon entropy and variety of surrounding POIs within a 200 m radius.	3.47	1.50
AV500	The gas station has an AV500 score of 4.10, signifying high Shannon entropy and variety of surrounding POIs within a 200–500 m radius.	4.10	1.62
GSA	The GSA score is imputed regionally.	–	–

Table 2 Regional pillar scores for Vienna (AT13)

Region	SSQ	AD200	AV200	AV500	GSA	GSI
AT-13, Wien	0.980	1.00	1.00	1.00	1.00	0.996

3.2 Overview of the Regions

Figure 4 presents the spatial distribution of the GSI across the four geographic groups covered by the study. The maps reveal substantial variation in gas-station infrastructure within and across countries and highlight spatial patterns consistent with differences in regional development.

In Europe, the GSI displays a broad core-periphery pattern, with relatively high values in parts of Central Europe, including Austria, Slovenia, and northern Italy, and lower values across several regions in the Balkans. East Asia exhibits particularly high GSI values in major urban and transport corridors, including the Tokaido corridor in Japan and the Seoul Capital Area in South Korea, where dense transport networks and concentrated service activity are reflected in the gas-station infrastructure.

The South American and South African cases display a different spatial configuration, characterised by large contrasts between major metropolitan and economically active regions and more sparsely served peripheral areas. In Brazil and Chile, relatively low GSI values are observed across extensive interior territories, while higher values are concentrated around major urban and economic centres such as São Paulo and Santiago and in more densely developed coastal areas. Similarly, in South Africa, higher GSI values are concentrated in economically important regions such as Gauteng and the Western Cape, whereas several more rural provinces display substantially lower levels of gas-station infrastructure.

These descriptive patterns suggest that the GSI captures meaningful spatial variation in consumer-facing infrastructure and service environments at the subnational

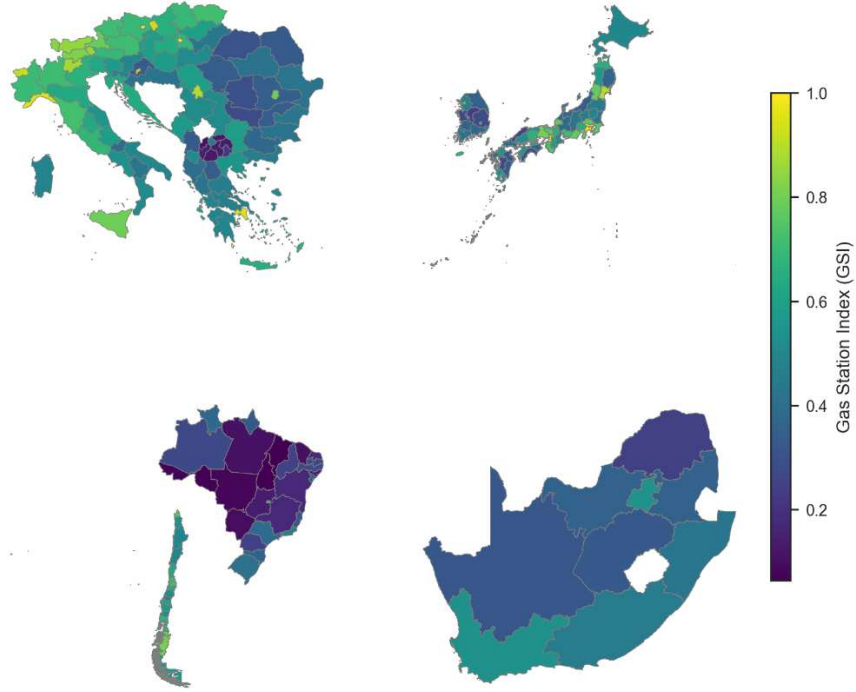


Fig. 4 Gas Station Index (GSI) scores across four continents

level. Section 4 examines whether these patterns systematically correspond to differences in regional economic development and how the GSI's explanatory performance compares with established alternatives such as nighttime lights.

4 Empirical Evaluation of the Gas Station Index

This section evaluates the empirical relationship between the Gas Station Index (GSI) and regional GDP per capita. The analysis proceeds in three steps. First, we assess the strength and form of the relationship between the GSI and regional economic output, comparing a pooled specification with models that account for country-specific heterogeneity. Second, we examine the relationship between the GSI and nighttime lights (NTL) to determine whether the two indicators capture overlapping or complementary dimensions of regional economic activity. Third, we conduct a series of diagnostic tests to assess linearity, variance stability, residual behaviour, and overall model adequacy.

We begin by visualising the relationship between the GSI and regional economic output. Although the pooled data reveal a positive association, cross-country comparisons are affected by substantial differences in national income levels, price structures, economic composition, and historically accumulated infrastructure. Figure 5 illustrates how accounting for country-specific heterogeneity sharpens the relationship between

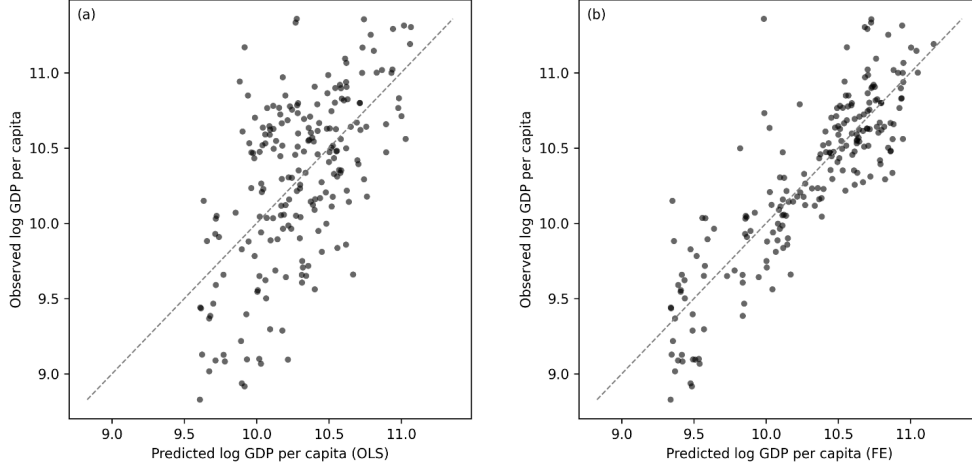


Fig. 5 The role of country-specific heterogeneity in the relationship between the GSI and regional GDP per capita. Panel (a) shows the pooled OLS relationship, with substantial vertical dispersion reflecting cross-country heterogeneity. Panel (b) shows the relationship after accounting for country fixed effects, revealing a substantially clearer association between the Gas Station Index and regional GDP per capita.

gas-station infrastructure and regional GDP per capita and allows the analysis to focus more closely on within-country differences in regional development.

4.1 Model Specification and Explanatory Performance

To evaluate the relationship between the Gas Station Index and regional economic development, we estimate a sequence of regression models in which the dependent variable is the logarithm of regional GDP per capita in purchasing-power terms. Table 3 reports the results, progressing from a pooled specification to models incorporating country fixed effects, population density, and nighttime lights.

The comparison between the pooled OLS specification in Column 1 and the country fixed-effects specification in Column 2 highlights the importance of accounting for national heterogeneity. In the pooled model, the GSI is positively and statistically significantly associated with regional GDP per capita ($\beta = 1.560$, $p < 0.01$), while the model explains approximately 36% of the variation in the dependent variable. This specification, however, combines within-country regional variation with substantial differences in average income and economic structure across countries.

Introducing country fixed effects in Model 2 substantially improves model fit, increasing the R^2 to 0.724. The GSI coefficient remains positive and statistically significant ($\beta = 0.743$, $p < 0.05$). This result indicates that the relationship between the GSI and regional GDP per capita is not driven solely by differences between high- and low-income countries. Even after controlling for time-invariant country-specific characteristics, regions with higher GSI values tend to have higher GDP per capita than other regions within the same country.

An important concern with infrastructure-based indicators is that they may primarily reflect urbanisation and population concentration rather than economic

Table 3 Regression Estimates of the Relationship between the GSI and Regional GDP per Capita

Variable	(1) Global OLS	(2) Country Fixed Effects	(3) + Population Density Control	(4) + Nighttime Lights
Gas Station Index (GSI)	1.560*** (0.138)	0.743** (0.309)	0.836** (0.363)	0.928** (0.361)
Log Population Density			-0.029 (0.045)	
Log Nighttime Lights				0.330*** (0.080)
Constant	9.507*** (0.086)	9.485*** (0.127)	9.558*** (0.157)	10.337*** (0.163)
Standardized β GSI				0.202
Standardized β NTL				0.199
Country Fixed Effects	No	Yes	Yes	Yes
Observations	207	207	207	207
Adjusted R^2	0.357	0.724	0.724	0.764

Note. Dependent variable is log GDP per capita (PPP adjusted). Standard errors (in parentheses) are clustered at the country level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

intensity. Model 3 therefore adds the logarithm of population density as an additional control. The coefficient on population density is small and statistically insignificant ($\beta = -0.029$), whereas the GSI coefficient increases slightly to 0.836 and remains statistically significant ($p < 0.05$). This suggests that the information contained in the GSI extends beyond simple demographic concentration. In particular, the index incorporates service quality, amenity intensity and diversity, and accessibility, allowing it to distinguish between population concentration and the broader commercial environment associated with regional economic development.

Model 4 introduces nighttime lights alongside the GSI within the country fixed-effects framework. Nighttime lights are measured for the same regions using the 2023 VIIRS VNL composite (Elvidge et al. 2017). Both indicators remain positively associated with regional GDP per capita when entered jointly. Because the two variables are measured on different scales, their raw coefficients are not directly comparable ($\beta_{\text{GSI}} = 0.928$, and $\beta_{\text{NTL}} = 0.330$). Standardising the variables, however, produces coefficients of 0.202 for the GSI and 0.199 for nighttime lights. The ratio of the two standardised coefficients is approximately 1.01, indicating very similar conditional associations with regional GDP per capita in the joint specification.

This finding is particularly important for interpreting the GSI. Its explanatory contribution does not disappear once nighttime lights are included in the model, suggesting that ground-level service infrastructure contains information about regional economic development that is not fully captured by remotely sensed luminosity. The following subsection examines the relationship between the two indicators more closely.

4.2 Complementarity between the GSI and Nighttime Lights

The results from Model 4 indicate that the GSI and nighttime lights contribute remarkably similarly to explaining regional GDP per capita once both variables are standardised. This raises an important question: do the two indicators capture essentially the same underlying economic signal, or do they reflect different dimensions of regional development?

The correlation analysis points toward the latter interpretation. Across the full sample, the correlation between the GSI and nighttime lights is close to zero ($r = -0.027$). When the comparison is made within countries, the correlation is moderately negative ($r = -0.251$). Thus, despite their similar associations with regional GDP per capita, the two indicators are only weakly related.

This result suggests that the GSI and nighttime lights capture different aspects of regional economic activity. Nighttime lights primarily reflect luminosity generated by settlements, production, infrastructure, and other sources of artificial lighting. The GSI, by contrast, reflects consumer-facing infrastructure, mobility, accessibility, station-level service quality, and the density and diversity of surrounding amenities. Together, they offer a broader perspective on regional development than either indicator alone.

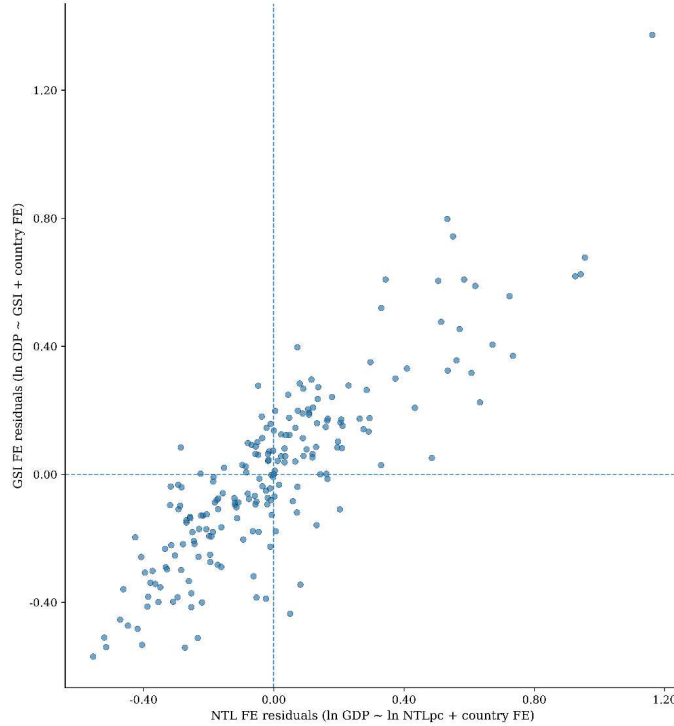


Fig. 6 Scatter Plot of Residuals of Gas Station Index and Nighttime Lights

Figure 6 further examines this complementarity by comparing the residual patterns associated with the two measures. The residuals often move in different directions, indicating that the two indicators do not systematically make the same prediction errors. In some regions, nighttime lights imply a higher level of economic activity than observed GDP would suggest, while the GSI provides a lower estimate; in others, the opposite occurs. Such differences are consistent with the possibility that the two indicators respond differently to specific regional characteristics, including urban form, infrastructure intensity, economic specialisation, and the spatial concentration of activity.

A quadrant decomposition of the residuals provides an additional perspective. A substantial share of regions lies in quadrants where both proxies deviate from observed GDP in the same direction, suggesting that neither measure fully captures some regional characteristics. The off-diagonal quadrants are particularly informative because they identify regions in which the two indicators provide contrasting signals. These cases suggest that discrepancies between the GSI and nighttime lights may contain economically meaningful information about the structure of regional development rather than representing measurement noise alone.

Taken together, these results support interpreting the GSI and nighttime lights as complementary rather than competing indicators. Their similar explanatory strength combined with their relatively weak correlation suggests that ground-level infrastructure and remotely sensed luminosity capture partly distinct dimensions of regional economic activity.

4.3 Diagnostic Tests and Functional-Form Assessment

To assess the adequacy of the empirical specification and the stability of the relationship between the GSI and regional GDP per capita, Figure 7 presents four diagnostic exercises: an assessment of linearity, an examination of residual variance, a comparison of residual distributions, and an analysis of country-specific residual patterns.

Panel (a) plots the residuals from the fixed-effects model against the GSI. The fitted curve indicates a broadly linear relationship across most of the GSI distribution, although some flattening is visible in the middle range of the index (approximately $\text{GSI} = 0.4\text{--}0.7$). This pattern may indicate weak diminishing returns to gas-station infrastructure: once a region reaches a relatively high level of infrastructure and service provision, further improvements may be associated with progressively smaller differences in GDP per capita. Nevertheless, the deviations from linearity are modest, suggesting that the linear specification provides a reasonable and readily interpretable approximation of the relationship.

Panel (b) plots the fixed-effects residuals against the fitted values. Residual dispersion is broadly similar across the predicted income range, with no pronounced funnel-shaped pattern or systematic increase in variance at higher levels of predicted GDP per capita. Although some heterogeneity is unavoidable in a cross-regional dataset spanning countries with very different economic structures, the graphical evidence does not indicate severe heteroscedasticity.

Panel (c) compares the distributions of residuals from the pooled OLS and country fixed-effects models. The fixed-effects residuals are more tightly concentrated around

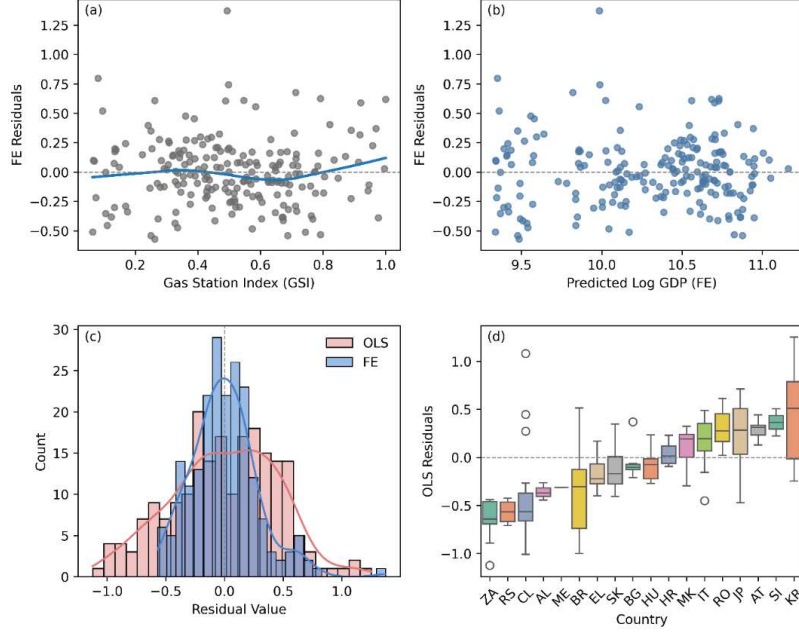


Fig. 7 Regression Diagnostics for the GSI-GDP Model

zero than those from the pooled model and are more symmetric. This improvement is consistent with the view that country-specific effects absorb much of the structural heterogeneity in the global sample.

Finally, Panel (d) presents pooled OLS residuals by country, showing the extent to which a single global relationship systematically over- or underpredicts regional GDP per capita in specific national contexts. South Africa, Chile, and Serbia tend to show predominantly negative residuals, indicating GDP per capita below the level predicted by the global GSI relationship. By contrast, Austria, Slovenia, and South Korea show predominantly positive residuals, indicating higher GDP per capita than the pooled relationship implies. These systematic country-level differences reinforce the importance of accounting for national heterogeneity. The country fixed-effects specification therefore provides a more appropriate framework for evaluating the relationship between the GSI and regional economic development within the multi-country sample.

5 Spatial Patterns and Regional Typologies

This section extends the empirical analysis by examining the spatial and structural patterns underlying the relationship between the Gas Station Index (GSI) and regional economic outcomes. First, we analyse the spatial distribution of residuals from the country fixed-effects model to identify regions whose GDP per capita is systematically higher or lower than expected based on their GSI. Second, we use a bivariate GSI-GDP framework to classify regions by their relative positions in infrastructure and income. Finally, we compare the residual patterns generated by the GSI and nighttime

lights (NTL) models to identify regional settings in which the two indicators provide different signals about economic activity. Together, these analyses help clarify what the GSI captures, where its explanatory power is strongest, and where its limitations differ from those of nighttime lights.

5.1 Spatial Patterns in Regional Performance

The spatial distribution of residuals from the country fixed-effects model provides additional insight into the relationship between gas-station infrastructure and regional economic performance. Figure 8 maps these residuals, with positive values indicating regions whose GDP per capita is higher than predicted by their GSI and negative values indicating regions whose GDP per capita is lower than predicted.

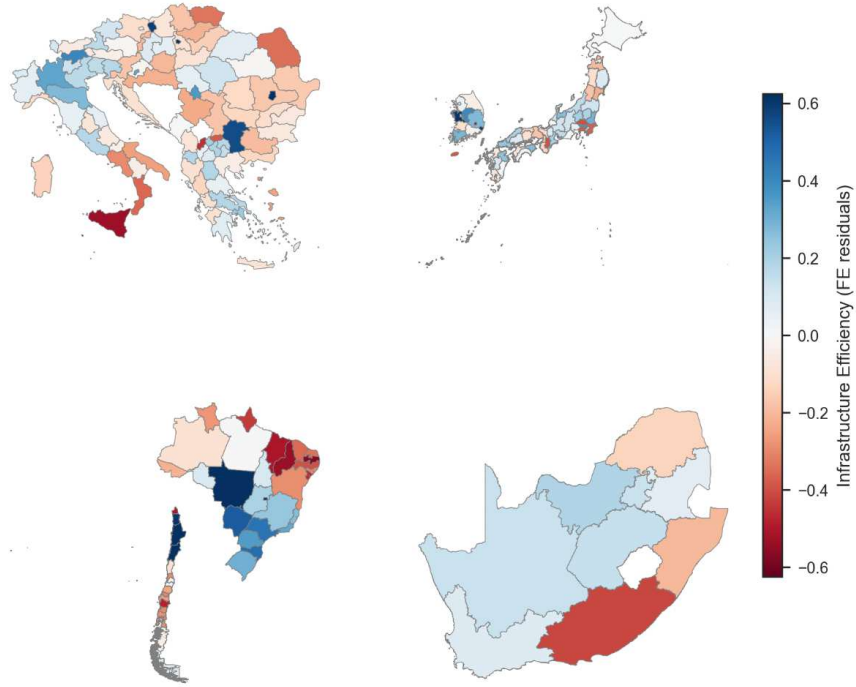


Fig. 8 Spatial Distribution of Fixed-Effects Residuals: Infrastructure-Output Efficiency Across Regions

Because country fixed effects absorb differences in average national income and other time-invariant country-specific characteristics, the residuals primarily reflect within-country variation. They should therefore be interpreted as measures of relative regional performance conditional on the observed level of gas-station infrastructure, rather than as direct measures of economic efficiency.

In Europe, positive residuals are concentrated in several Central European and northern Italian regions, including parts of Austria, Slovenia, Hungary, Veneto, and Emilia-Romagna. By contrast, negative residuals are more common in parts of southern Italy, Bulgaria, and Greece. These patterns align with persistent within-country and cross-regional differences in economic performance and suggest that regions with similar levels of gas-station infrastructure may generate substantially different measured output.

In East Asia, Japanese regions generally display residuals close to zero or moderately positive, with stronger positive deviations in Tokyo and Aichi Prefecture. South Korea exhibits greater internal heterogeneity. The Seoul–Gyeonggi metropolitan area lies relatively close to GSI-predicted levels, while several peripheral regions show negative residuals. This pattern is consistent with the strong spatial concentration of high-value economic activity within the country’s principal metropolitan core.

In South America, Chile displays predominantly positive residuals in several regions, including Antofagasta and parts of the central metropolitan corridor. Brazil exhibits considerably greater regional dispersion. States such as Santa Catarina and Mato Grosso do Sul perform relatively well compared with their GSI values, whereas Maranhão, Pará, and Piauí record substantial negative deviations. These differences are consistent with the pronounced spatial heterogeneity of economic activity within Brazil.

In South Africa, several provinces display negative residuals, indicating GDP per capita below the level predicted by their gas-station infrastructure. Gauteng is an important exception, remaining close to or slightly above its predicted level. This pattern is consistent with the strong concentration of economic activity in the Johannesburg–Pretoria metropolitan region.

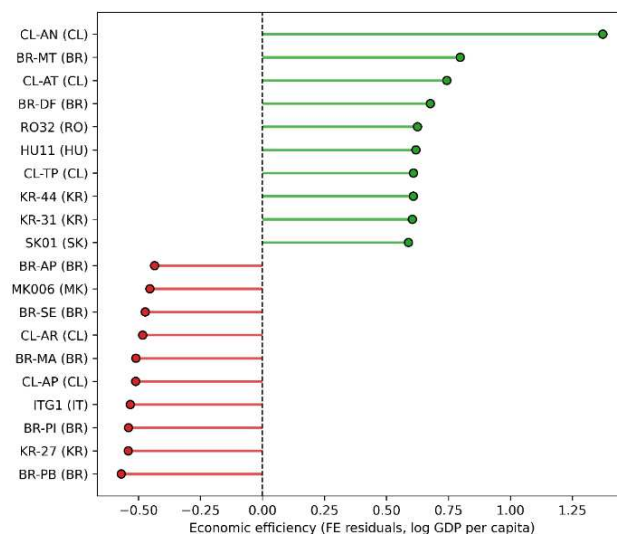


Fig. 9 Largest Overperformance and Underperformance among the Regions

Figure 9 presents the regions with the largest positive and negative residuals from Model 2. Among the strongest positive deviations are Antofagasta (CL-AN), Mato Grosso (BR-MT), Atacama (CL-AT), and Brasília/Federal District (BR-DF). These regions are characterised by economic structures that can generate substantial value added without a proportionate expansion of consumer-facing infrastructure, including mining, agribusiness, and administrative activity. At the opposite end of the distribution, regions such as Paraíba (BR-PB), Piauí (BR-PI), Gyeongsangbuk-do (KR-27), and the Polog Region of North Macedonia (MK006) record large negative residuals. These cases indicate that relatively developed service infrastructure does not necessarily translate into correspondingly high levels of measured regional output.

Overall, the residual analysis shows that the relationship between infrastructure and economic output is systematic but not mechanical. The GSI captures an important component of regional development, but differences in sectoral composition, productivity, institutional context, and other region-specific characteristics influence the extent to which observable infrastructure is associated with measured GDP per capita.

5.2 GSI–GDP Regional Typologies

Figure 10 presents a bivariate classification of regions by GSI and GDP per capita. The framework allows regions to be compared simultaneously along two dimensions: consumer-facing infrastructure and measured economic output.

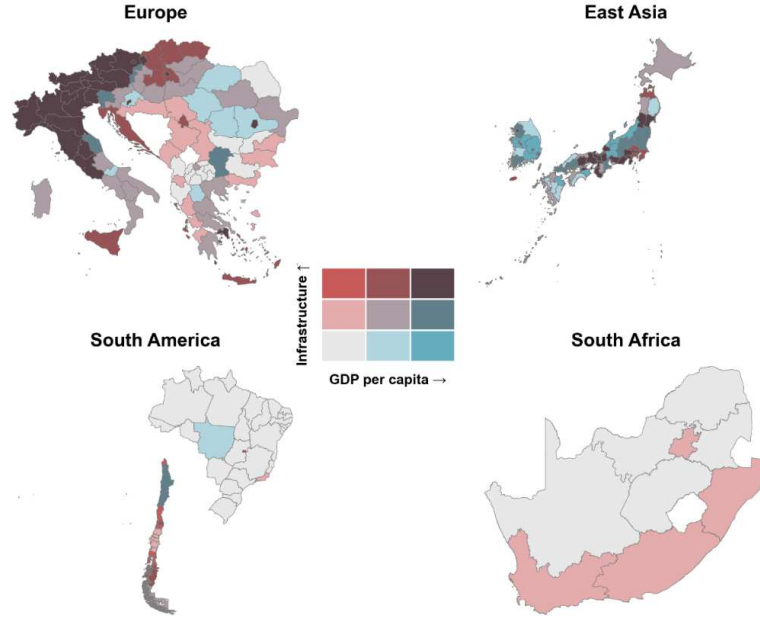


Fig. 10 Identifying Development Typologies Using the Gas Station Index

Regions in the upper-right part of the matrix combine high GSI values with high GDP per capita, while regions in the lower-left combine relatively limited gas-station infrastructure with low income levels. These cases represent broad alignment between infrastructure and economic development. By contrast, regions located away from the main diagonal display a greater mismatch between the two dimensions and are therefore particularly informative for understanding the limits of infrastructure-based measures.

In Europe, many regions in Italy, Austria, and Hungary are positioned relatively close to the diagonal, suggesting broad correspondence between GSI levels and regional income. However, several notable deviations emerge. Sicily differs from many northern and central Italian regions, while Croatian, Serbian, and Romanian regions display greater dispersion around the diagonal. These cases indicate that similar levels of gas-station infrastructure can coexist with substantially different economic outcomes.

A similar pattern is observed in East Asia. In South Korea, the small administrative regions containing major metropolitan centres tend to occupy the upper end of the distribution, while several other regions display GDP per capita that is relatively high compared with their GSI values. In Japan, a large proportion of regions lies relatively close to the diagonal, although a number of economically specialised or highly urbanised regions exhibit noticeable deviations.

In South America, many Brazilian regions are concentrated in the lower part of the matrix, reflecting relatively low GSI and GDP levels. Some regions, however, diverge substantially from this pattern. Mato Grosso records comparatively high GDP per capita relative to its GSI, while Rio de Janeiro and Brasília exhibit combinations of infrastructure and output that differ from the dominant national pattern. Chile displays greater dispersion across the matrix, illustrating the substantial heterogeneity of regional development within the country.

South Africa presents another distinctive configuration. Several provinces combine relatively moderate levels of gas-station infrastructure with comparatively low GDP per capita. This suggests that consumer-facing infrastructure alone is not sufficient to overcome broader structural constraints on regional economic performance.

The bivariate analysis therefore complements the regression results by showing where the relationship between infrastructure and income aligns and where it diverges. These deviations are particularly useful because they highlight regions in which economic structure, productivity, or other local characteristics may weaken the correspondence between observable service infrastructure and measured output.

5.3 Comparative Regional Typologies from GSI and Nighttime Lights

Figure 11 extends the analysis by comparing residuals from the GSI and NTL models. The figure focuses on the 20 regions with the largest prediction errors under the nighttime-lights specification and reports the corresponding GSI residuals for comparison. This provides a direct way to assess whether the two indicators perform similarly in the same regions or whether one measure provides additional information where the other performs less well.

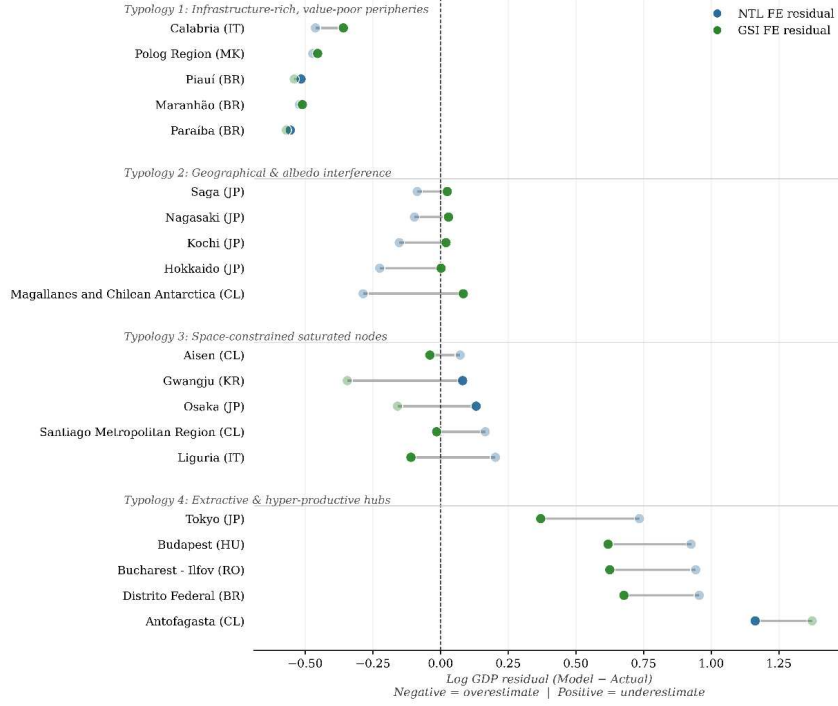


Fig. 11 Comparative Residual Performance of the Gas Station Index and Nighttime Lights

The comparison reveals systematic differences between observed regional GDP per capita and the values implied by the two proxy measures. Rather than treating these deviations as purely random error, we can group the patterns into several economically interpretable regional typologies. These typologies should not be interpreted as definitive causal classifications, but they provide a useful framework for understanding when ground-level infrastructure and satellite-based luminosity generate different signals.

Typology 1: Infrastructure-Rich Regions with Comparatively Low Measured Output

The first group includes regions such as Calabria in Italy, the Polog Region in North Macedonia, and Piauí, Maranhão, and Paraíba in Brazil. In these cases, both the GSI and NTL models tend to predict higher GDP per capita than official records.

These regions combine visible infrastructure, mobility, and settlement activity with comparatively low measured economic output. The fact that both proxies deviate in the same direction suggests that the discrepancy is unlikely to be specific to either the gas-station or nighttime-lights measure. Instead, it may reflect a broader disconnect between observable economic activity and formally measured value added.

Several mechanisms may contribute to this pattern, including informal economic activity, remittance- or transfer-supported consumption, relatively low productivity,

and differences in regional income measurement. The relative importance of these mechanisms likely varies substantially across regions and cannot be established from the residual analysis alone. Nevertheless, the consistent direction of the GSI and NTL residuals suggests these regions warrant particular attention when interpreting conventional measures of regional development.

Typology 2: Regions Potentially Affected by Geographic and Optical Distortions

The second group includes regions such as Saga, Nagasaki, Kochi, and Hokkaido in Japan, together with Magallanes and Chilean Antarctica in Chile. In these cases, the nighttime-lights model exhibits comparatively large deviations, while the GSI residuals tend to be closer to zero.

One possible explanation is that geographic and environmental characteristics affect the relationship between observed luminosity and economic activity. Coastal morphology, large water surfaces, snow cover, and the spatial configuration of ports and settlements can influence how satellites observe nighttime luminosity. Because the GSI is based on fixed, land-based service infrastructure, amenity density, and accessibility, it may be less sensitive to these particular optical and geographic effects.

The smaller GSI residuals in several of these regions suggest that ground-level infrastructure can provide useful complementary information in environments where remotely sensed luminosity may be influenced by physical geography.

Typology 3: Space-Constrained and Highly Saturated Urban Regions

A third group consists of densely developed and spatially constrained regions such as Gwangju, Osaka, the Santiago Metropolitan Region, Liguria, and selected high-density Japanese regions. In these settings, both indicators face measurement challenges, although for different reasons.

Nighttime lights may become less informative in highly illuminated urban environments because additional economic activity does not necessarily generate proportionate increases in observed luminosity. The GSI can face a different form of saturation: once gas-station infrastructure and surrounding service density reach very high levels, additional increases in economic output may occur without corresponding expansion of the physical infrastructure captured by the index.

Consequently, neither indicator consistently dominates in these environments. In some highly urbanised regions, the GSI more closely approximates observed GDP per capita, whereas in others nighttime lights perform better. This result highlights the importance of treating the two measures as complementary, particularly in mature metropolitan economies.

Typology 4: High-Value and Specialised Economic Hubs

The final group includes regions such as Tokyo, Budapest, Bucharest–Ilfov, the Federal District of Brazil, and Antofagasta in Chile, where both the GSI and NTL models tend to predict lower GDP per capita than is observed.

In specialised extractive regions such as Antofagasta, capital-intensive mining activities can generate exceptionally high value added while occupying a relatively limited physical footprint and not necessarily supporting a proportionate expansion of local consumer-facing infrastructure. In such cases, nighttime lights may capture some industrial and transport activity that is less visible in the GSI, although both indicators may still substantially underestimate regional output.

A different mechanism may operate in high-income metropolitan regions such as Tokyo, Budapest, and Bucharest–Ilfov. These economies concentrate substantial value added in finance, advanced services, public administration, and knowledge-intensive activities. Such activities can generate very high levels of GDP without corresponding increases in either luminosity or physical service infrastructure. In these cases, both indicators face saturation, although the GSI may retain additional variation through service quality, amenity diversity, and accessibility.

Taken together, these typologies show that the Gas Station Index does not simply reproduce the information contained in nighttime lights. The two indicators capture different dimensions of regional economic activity and exhibit different limitations across spatial and economic contexts. Nighttime lights provide information on the spatial distribution of artificial luminosity, whereas the GSI reflects the organisation of consumer-facing infrastructure, mobility, accessibility, and local service environments.

Their joint evaluation therefore provides a richer interpretation of regional development than either indicator alone. In particular, discrepancies between the two measures can help identify regions characterised by specialised production structures, highly concentrated metropolitan activity, unusual geographic conditions, or a weak correspondence between observable infrastructure and formally measured output. These findings reinforce the interpretation of the GSI as a complementary ground-level measure of regional development rather than a substitute for nighttime lights or official regional GDP statistics.

6 Conclusions

This study introduces the Gas Station Index (GSI) as a bottom-up, infrastructure-based indicator of regional economic development. Using geospatial information on approximately 100,000 gas stations across 207 regions in 18 countries spanning Europe, East Asia, South America, and Africa, we show that a composite measure combining station service quality, surrounding amenity intensity and diversity, and accessibility contains substantial information about regional economic conditions. In the preferred cross-sectional specifications, the GSI is strongly associated with regional GDP per capita and, after accounting for country-specific heterogeneity, explains a large share of the observed variation in regional income. This result highlights how much everyday commercial infrastructure reflects broader differences in regional development.

The comparison with nighttime lights provides an important second finding. The GSI and nighttime lights show similar explanatory strength in the joint fixed-effects specification, yet they are only weakly correlated. This suggests that the two indicators capture partly distinct dimensions of regional economic activity. Nighttime lights primarily reflect the spatial distribution of artificial luminosity, whereas the GSI

captures ground-level service provision, mobility, accessibility, and the density and diversity of surrounding commercial activity. The GSI therefore complements rather than replicates satellite-based measures and can provide additional information in settings where luminosity is affected by saturation, geographic conditions, or differences in the relationship between lighting and economic activity.

The spatial analysis also reveals important limits to infrastructure-based proxies. In regions dominated by capital-intensive, extractive, administrative, or other highly productive activities concentrated in a relatively small physical footprint, both the GSI and nighttime lights may substantially diverge from measured GDP per capita. Similar challenges arise in highly urbanised metropolitan regions, where economic output can increase without proportional expansion in either service infrastructure or observable luminosity. These deviations should not be treated simply as statistical noise. Rather, they often point to meaningful differences in sectoral composition, spatial organisation, productivity, and the relationship between physical infrastructure and value creation. Proxy-based measures of regional development should therefore be interpreted alongside information on regional economic structure and institutional context.

The study also has several limitations. First, the GSI relies on open geospatial data whose completeness, consistency, and update frequency may differ across countries and regions. Although the index performs well across a heterogeneous international sample, variation in mapping intensity may still affect individual station and regional scores. Second, the analysis is cross-sectional and therefore evaluates the GSI primarily as a measure of spatial differences in regional development rather than economic change over time. Third, using regional GDP per capita as the validation benchmark means the empirical results inevitably inherit some of the measurement limitations of official regional accounts. Finally, the equal weighting of the five GSI pillars provides a transparent and easily interpretable benchmark, but alternative weighting schemes may contain additional information and should be examined in future research.

These limitations point directly to several promising extensions. Constructing the GSI repeatedly over time would make it possible to evaluate whether changes in gas-station infrastructure and surrounding amenities can track short-run changes in regional economic activity and, eventually, support nowcasting applications. A panel version of the index would also allow the investigation of lead-lag relationships and structural changes in regional development. Applying the GSI at finer spatial resolutions would open further possibilities for analysing intra-regional inequality, urban-rural gradients, development corridors, and highly localised patterns of economic activity. Future work could also assess alternative weighting procedures, test the stability of individual pillars across countries, and examine whether combining the GSI with nighttime lights and other geospatial indicators improves measurement further.

More broadly, the findings demonstrate that the economic information embedded in everyday commercial infrastructure can be used systematically to study regional development. By observing economic activity from the ground up through gas stations, surrounding amenities, and accessibility, the GSI captures patterns of consumption, mobility, service provision, and private infrastructure investment that are difficult to

observe through conventional regional statistics or satellite luminosity alone. Because it is based on openly available, scalable geospatial data, the index offers a transparent, relatively low-cost complement to existing measures of regional economic activity. As the coverage and consistency of open geospatial data continue to improve, ground-level indicators based on everyday infrastructure may provide an increasingly useful tool for measuring, comparing, and interpreting economic development across space.

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