TRAFFIC, MODELLING

Spatial Heterogeneity and Highway-Specific Traffic Demand Modelling in South-Eastern Nigeria: Evidence from Five Inter-State Highways

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Abstract

Reliable understanding of spatial differences in highway traffic demand is essential for highway planning, pavement management, infrastructure investment, and transport-system development, particularly where traffic-count observations are geographically limited. This research investigates spatial heterogeneity in annual average daily traffic (AADT) and develops highway-specific traffic-demand models for five major inter-state highways in South-Eastern Nigeria: Umuahia-Ikot Ekpene, Onitsha-Owerri, Abakaliki-Ogoja, Enugu-Port Harcourt, and Owerri-Port Harcourt. A longitudinal dataset of 100 highway-year observations spanning 2001 to 2020 was analyzed using descriptive spatial profiling, highway-level variation measures, group-difference testing, pooled highway-effects regression, highway-specific log-linear regression, and interaction modelling. The results reveal substantial spatial heterogeneity. Mean AADT ranged from 588,709 PCU/day on Abakaliki-Ogoja to 2,202,095 PCU/day on Enugu-Port Harcourt, and highway differences accounted for approximately 82.6% of the unadjusted variation in AADT. The highway-specific models also differed markedly in explanatory structure. Passenger population density was particularly influential on Umuahia-Ikot Ekpene and Abakaliki-Ogoja, whereas GDP showed the strongest statistically significant association on Enugu-Port Harcourt. A pooled interaction model confirmed that the relationships between population density, GDP, and AADT varied significantly across highways (robust Wald $\chi^2 = 34.88$, $p < 0.001$), providing evidence of spatially non-stationary traffic-demand relationships. These findings demonstrate that a single regional traffic-demand equation may conceal important highway-specific differences. Inter-state highway planning in South-Eastern Nigeria should therefore account for spatially differentiated demand structures. The study offers an empirical basis for more targeted highway planning, pavement management, and investment prioritization in comparable data-constrained contexts.

Keywords: annual average daily traffic; interstate highways; spatial heterogeneity; South-Eastern Nigeria; traffic-demand modelling

1 Introduction

Annual Average Daily Traffic (AADT) is a fundamental measure of highway utilization and is widely used in transportation planning, infrastructure design, pavement management, environmental assessment and traffic operations. Reliable traffic-volume information provides an empirical basis for assessing roadway demand, identifying infrastructure requirements and supporting investment decisions. However, systematic traffic monitoring is expensive and is frequently concentrated on major roads or selected count locations, leaving substantial spatial gaps in traffic information (Apronti et al., 2016; Fu et al., 2017; Mathew and Pulugurtha, 2021). Recent research has consequently

placed increasing emphasis on statistical, geospatial and machine-learning approaches for estimating traffic volumes where direct observations are incomplete. AADT is not spatially uniform because highway traffic is influenced by differences in demographic concentration, economic activity, road characteristics, land use, accessibility, network connectivity and highway function. Studies conducted in different geographical settings have demonstrated that socioeconomic and roadway characteristics can have substantial relationships with traffic volumes, but that these relationships may differ according to road class and location (Sfyridis and Agnolucci, 2020, 2023). In particular et al. (2023) found that the associations between explanatory variables and AADT varied across road classes and vehicle types, indicating that traffic-demand relationships cannot necessarily be assumed to be spatially constant.

The importance of spatial variation has also been demonstrated in geospatial AADT modelling. Pulugurtha and Mathew (2021) found that road density, land use, proximity to higher-classified roads and neighbouring traffic volumes influenced local-road AADT, while geographically weighted regression provided greater capacity to represent geographic variation than conventional global regression. Similarly et al. (2021) demonstrated the relevance of geospatial, socioeconomic and demographic information for estimating AADT at locations without direct traffic counts.

More recent work has reinforced the importance of incorporating spatial structure explicitly into traffic estimation. Ma et al. (2026), for example, developed a large-scale AADT estimation framework incorporating contextual and spatial-statistical features and spatially informed validation, demonstrating that traffic estimation can benefit from explicit treatment of spatial dependencies and heterogeneity. Their findings are particularly relevant to regions with sparse traffic-monitoring networks, where assuming that observations are spatially interchangeable can lead to biased or poorly generalized estimates.

Economic and demographic characteristics are also relevant to highway demand. Passenger population concentration can increase trip generation and the movement of people and goods, while economic activity can influence travel intensity through employment, commercial activity, freight movement and household mobility. Evidence from Nigeria similarly indicates that passenger population density, road characteristics and economic conditions are associated with road-transport outcomes, while international evidence shows that GDP and road characteristics can be important determinants of travel demand (Akinyemi, 2023; Chi, 2016).

Despite this growing literature, relatively limited empirical attention has been given to highway-specific spatial heterogeneity in inter-state traffic demand in South-Eastern Nigeria. Existing traffic studies often treat the region as a single analytical unit or concentrate on individual roads, while a comparative longitudinal examination of several strategically important inter-state highways can reveal whether the socioeconomic relationships observed at the regional level are consistent across highways.

This distinction is important because the five highways examined in this study perform different transportation functions and traverse areas with different demographic and economic characteristics. Consequently, a regional model that estimates a single average relationship between socioeconomic conditions and AADT may mask meaningful differences in highway-specific demand responses.

1.1 Research gap

The principal gap addressed by this study is therefore methodological and geographical. Previous AADT studies have established the importance of socioeconomic, demographic and roadway variables, and recent research has increasingly incorporated spatial modelling techniques. However, evidence remains limited on whether the magnitude and direction of traffic-demand relationships differ systematically among major inter-state highways in South-Eastern Nigeria.

This study addresses that gap by treating each highway as a distinct spatial demand environment while retaining the longitudinal structure of the data. Rather than focusing primarily on prediction accuracy, the analysis investigates the extent of highway heterogeneity and estimates highway-specific demand relationships.

1.2 Aim and objectives

The aim of this study is to investigate spatial heterogeneity in AADT and develop highway-specific traffic-demand models for five major inter-state highways in South-Eastern Nigeria.

The specific objectives are to:

1. quantify differences in AADT levels and temporal variability among the five study highways;
2. assess the contribution of highway-level spatial differences to observed variation in AADT;
3. estimate highway-specific relationships between AADT and selected socioeconomic and demographic variables;
4. determine whether the relationships between GDP, passenger population density and AADT differ significantly across highways; and
5. discuss the implications of spatially heterogeneous traffic demand for highway planning and infrastructure management in South-Eastern Nigeria.

1.3 Literature review

1.3.1 AADT and highway demand modelling

AADT represents the average number of vehicles travelling along a roadway during a typical day over a specified year and constitutes one of the most widely used indicators of roadway utilization. Traffic-volume information is required for highway design, pavement management, safety analysis, environmental assessment and transportation planning (Apronti et al., 2016; Mathew and Pulugurtha, 2021). However, obtaining continuous traffic observations across an extensive road network is costly, making modelling an important alternative where direct counts are unavailable.

Several methodological approaches have been developed for AADT estimation. Fu et al. (2017) demonstrated that available geographic, census, traffic and vehicle-fleet information can be integrated to estimate AADT across an extensive national road network. Their work illustrates the potential for combining multiple data sources to overcome limitations in direct traffic-count coverage.

Pulugurtha and Mathew (2021) subsequently incorporated road density, land use, nearby-road traffic and socioeconomic characteristics into local-road AADT models. Their comparison of ordinary least squares and geographically weighted regression demonstrated that local relationships can differ spatially, supporting the use of approaches that recognize geographic variation.

1.3.2 Socioeconomic and demographic influences on traffic demand

Traffic demand is closely related to the spatial distribution of passenger population and economic activity. Higher passenger population density may increase the number of potential trips, while higher economic activity may generate additional passenger, commercial and freight movements. Sfyridis and Agnolucci (2023) found that socioeconomic and roadway characteristics were important correlates of AADT, while the strength of associations varied among road classes and vehicle categories. GDP can represent the scale of economic activity and therefore provide an indirect measure of potential trip generation. Similarly, passenger population density can capture the concentration of residents and associated mobility demand. These relationships are not necessarily uniform because the same increase in economic or demographic activity can produce different traffic responses depending on highway connectivity, highway function, urbanization and alternative-route availability.

Fuel price provides another potentially important demand variable. Travel-demand research indicates that vehicle travel can respond asymmetrically to fuel-price changes, although the magnitude of response depends on temporal and contextual conditions (Chi, 2016). In Nigeria, fuel-price changes are particularly relevant because road transport is strongly dependent on petroleum-based mobility, although fuel-price effects may be mediated by income, vehicle ownership, trip necessity and the availability of alternatives (Akinyemi, 2023).

1.3.3 Spatial heterogeneity in traffic demand

Spatial heterogeneity refers to systematic differences in the level or relationships of a phenomenon across geographic units. In traffic modelling, it may arise because roads serve different populations, economic centres, land-use structures, network functions and travel markets.

A global regression model assumes that a given predictor has the same coefficient across all observations. Such an assumption may be inappropriate where roads serve substantially different travel environments. Sfyridis and Agnolucci (2020) explicitly addressed spatial differentiation in AADT estimation by combining clustering and regression modelling, while their subsequent research showed that associations between explanatory factors and traffic volumes vary by road class and vehicle type.

The development of geographically weighted regression and related spatial approaches reflects the same conceptual issue: the relationship between a dependent variable and its explanatory variables may vary across geographic space. Pulugurtha and Mathew (2021) found that GWR could capture geospatial variations in local-road AADT more effectively than conventional OLS in their study area.

More recent AADT research has moved further towards explicit spatial feature engineering and spatially informed validation. Ma et al. (2026) incorporated spatial-statistical features into a large-scale AADT prediction framework and demonstrated that spatial heterogeneity and spatial dependence should be considered when predicting traffic volumes across heterogeneous road networks.

The present study adopts a more parsimonious approach appropriate for the available Nigerian longitudinal dataset. Instead of attempting fine-scale geospatial modelling with only five highways, spatial heterogeneity is operationalized at the highway level. The approach therefore identifies whether the five inter-state highways have different demand levels and whether their socioeconomic demand relationships differ.

2 Materials and methods

2.1 Study area and highway corridors

The study covers five major inter-state highways in South-Eastern Nigeria:

1. Umuahia–Ikot Ekpene;
2. Onitsha–Owerri;
3. Abakaliki–Ogoja;
4. Enugu–Port Harcourt; and
5. Owerri–Port Harcourt.

The highways provide important inter-state connections between major urban, commercial and administrative centres in the region. They differ in length, number of lanes, traffic intensity, demographic environment and highway function, providing an appropriate basis for examining spatial heterogeneity in traffic demand.

2.2 Data structure

The empirical analysis uses 100 complete highway-year observations covering five highways over 20 years, from 2001 to 2020. The dependent variable is AADT measured in PCU/day. The explanatory variables include GDP, passenger population density, fuel price, pothole volume, annual rainfall, vehicle registration, number of lanes and rehabilitation events. Road length and number of lanes are also used to characterize the physical structure of the corridors.

The dataset contains one observation for each highway-year combination, thereby producing a balanced longitudinal structure of five highways × 20 years. The dataset used for the analysis is the cleaned study dataset supplied for the research.

Table 1 presents the variables used in the highway-specific analysis, showing the role of each in the models and the operational measure through which it was defined, with AADT as the dependent variable and the remaining economic, demographic, environmental, mobility, and highway-supply and condition indicators as explanatory or contextual factors.

Table 1. Variables and operational definitions used in the highway-specific analysis.

Variable	Role	Operational measure
AADT	Dependent variable	Annual average daily traffic (PCU/day)
GDP	Explanatory	Annual GDP (Naira)
Passenger population density	Explanatory	Persons/km/year
Fuel price	Explanatory	Annual fuel price (Naira/litre)
Pothole volume	Environmental/road condition	Pothole volume (m^3/km)
Rainfall	Environmental	Annual rainfall (mm)
Vehicle registration	Mobility indicator	Number of registered vehicles
Lanes	Highway supply	Number of traffic lanes
Road length	Highway characteristic	Highway length (km)
Rehabilitation	Infrastructure condition	Number of rehabilitation events

Table 1 summarizes the variables incorporated into the highway-specific analysis, distinguishing the dependent AADT measure from explanatory variables representing socioeconomic, environmental, mobility, highway-supply, and infrastructure characteristics. These operational measures provide a consistent basis for examining how differences in economic activity, population density, fuel prices, road conditions, rainfall, vehicle ownership, lane provision, highway length, and rehabilitation relate to traffic demand across the five inter-state highways.

2.3 Analytical framework

The analysis was organized into four stages.

First, descriptive statistics were calculated separately for each highway to quantify spatial differences in mean AADT, standard deviation, minimum and maximum traffic levels. The coefficient of variation (CV) was calculated as:

$$CV_j = \frac{SD_j}{AADT_j} \tag{1}$$

where *j* represents a highway.

Second, differences in AADT among highways were assessed using one-way analysis of variance as a descriptive measure of between-highway variation. Because the observations form a longitudinal dataset rather than independent cross-sectional samples, the ANOVA is interpreted primarily as an indicator of the magnitude of spatial differentiation rather than as a standalone causal test. A Kruskal–Wallis test was also used as a non-parametric robustness check.

Third, highway-specific log-linear models were estimated separately for each corridor:

$$\ln AADT_{j,t} = \alpha_j + \beta_{1,j} \ln GDP_{j,t} + \beta_{2,j} \ln PD_{j,t} + \beta_{3,j} \ln FP_t + \epsilon_{j,t} \tag{2}$$

where $AADT_{j,t}$ is traffic demand on corridor *j* in year *t*, $GDP_{j,t}$ is GDP, $PD_{j,t}$ is passenger population density and FP_t is fuel price.

The logarithmic specification allows coefficients to be interpreted approximately as elasticities. For example, a coefficient of 0.70 on population density indicates that a 1% increase in passenger population density is associated with an approximately 0.70% increase in AADT, holding the other modelled variables constant.

Fourth, a pooled interaction model was estimated to formally test whether the GDP and passenger population-density elasticities differed among highways:

$$\begin{aligned} \ln AADT_{j,t} = {} & \alpha + \beta_1 \ln GDP_{j,t} + \beta_2 \ln PD_{j,t} + \beta_3 \ln FP_t + \gamma_j + \delta_j \left[\ln GDP_{j,t} \times j \right] \\ & + \theta_j \left[\ln PD_{j,t} \times j \right] + \epsilon_{j,t} \end{aligned} \tag{3}$$

This specification allows the slopes of GDP and population density to vary across highways and therefore provides a direct test of spatially heterogeneous demand relationships.

2.4 Estimation and diagnostic procedures

HC3 heteroscedasticity-consistent standard errors were used for the regression estimates because the dataset contains substantial differences in traffic scale among highways. This approach provides more reliable inference when the assumption of constant residual variance is questionable.

Road length was not included as a conventional regression predictor because it is constant within each highway and therefore cannot identify a time-varying effect in the corridor-specific longitudinal models. Similarly, the number of lanes was used primarily as a highway characteristic because it is invariant for some highways and changes only during limited portions of the study period.

The modelling strategy was intentionally parsimonious because each highway-specific regression contains only 20 annual observations. A large number of predictors relative to the number of observations would increase parameter uncertainty and the risk of overfitting.

3 Results

3.1 Spatial differences in AADT

Table 2 summarizes the spatial variation in AADT across the five corridors from 2001 to 2020, reporting each highway's mean, standard deviation, coefficient of variation, and range of traffic volume alongside its mean number of lanes, highway length, and rehabilitation events.

Table 2. Spatial variation in AADT and selected highway characteristics, 2001–2020.

Highway	Mean AADT (PCU/day)	SD	CV	Min.	Max.	Mean lanes	Length (km)	Rehabilitation events
Enugu–Port Harcourt	2,202,095	357,844	0.163	1,263,635	2,733,585	3.60	210	41
Owerri–Port Harcourt	1,274,232	209,153	0.164	533,476	1,581,339	2.00	80	26
Onitsha–Owerri	1,273,647	216,380	0.170	897,216	1,684,165	3.60	97	34
Umuahia–Ikot Ekpene	1,226,869	203,114	0.166	911,316	1,555,769	2.00	49	23
Abakaliki–Ogoja	588,709	186,234	0.316	364,259	1,026,650	2.00	85	23

The results show a pronounced spatial gradient in traffic demand. Enugu–Port Harcourt recorded the highest mean AADT at 2,202,095 PCU/day, approximately 3.7 times the mean traffic level on Abakaliki–Ogoja. Owerri–Port Harcourt, Onitsha–Owerri and Umuahia–Ikot Ekpene recorded intermediate mean traffic levels of 1,274,232, 1,273,647 and 1,226,869 PCU/day, respectively. Abakaliki–Ogoja recorded the lowest mean AADT at 588,709 PCU/day and also exhibited the largest relative temporal variability, with a coefficient of variation of 0.316 compared with approximately 0.16–0.17 for the other four highways.

The differences are also reflected in the physical characteristics of the highways. Enugu–Port Harcourt is the longest highway in the dataset at 210 km and has an average of 3.60 lanes, while Umuahia–Ikot Ekpene and Owerri–Port Harcourt have two lanes on average. These characteristics do not by themselves establish causality, but they indicate that the highways operate within substantially different transportation environments.

3.2 Magnitude of between-highway heterogeneity

The one-way ANOVA produced an F-statistic of 112.50 with $p < 0.001$. The corresponding eta-squared statistic was 0.826, indicating that approximately 82.6% of the unadjusted variance in AADT was associated with differences among the five highway groups.

The non-parametric Kruskal–Wallis test produced a statistic of 71.80 ($p < 0.001$), providing a consistent indication that the distribution of AADT differs substantially among the highways.

These results provide strong descriptive evidence of highway-level heterogeneity. However, the statistics should not be interpreted as establishing a causal effect of highway location because observations within each highway are repeated over time.

Figure 1 presents the mean AADT recorded across the five study highway pavements over the 2001–2020 study period. The figure provides a comparative overview of the spatial variation in average traffic demand among the highways.

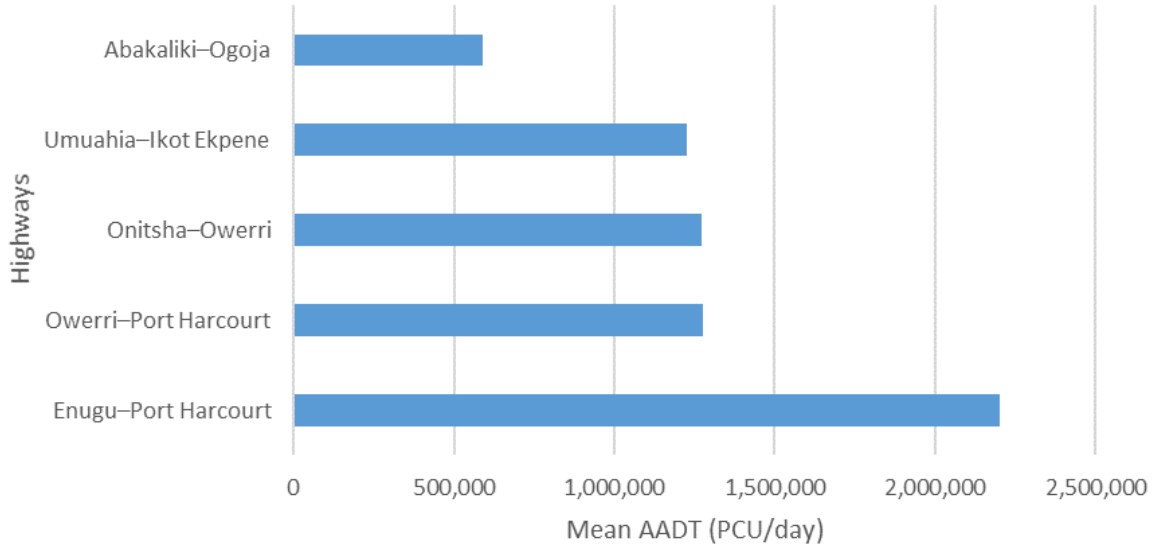


Figure 1. Mean AADT by highway corridor, 2001–2020.

Figure 1 shows substantial differences in mean AADT across the five highways, indicating pronounced spatial heterogeneity in traffic demand. The Enugu–Port Harcourt road recorded the highest mean AADT (2,202,095 PCU/day), whereas the Abakaliki–Ogoja highway recorded the lowest (588,709 PCU/day). The relatively high traffic volumes on the Enugu–Port Harcourt, Owerri–Port Harcourt and Onitsha–Owerri roads may reflect their greater roles in inter-state movement and commercial connectivity, while the lower volume on Abakaliki–Ogoja indicates comparatively lower traffic demand during the study period.

3.3 Temporal heterogeneity across highways

The five highways also differed in their response during the final year of the study period. Between 2019 and 2020, AADT declined by 40.9% on Umuahia–Ikot Ekpene, 43.3% on Onitsha–Owerri, 57.8% on Abakaliki–Ogoja, 48.9% on Enugu–Port Harcourt and 66.3% on Owerri–Port Harcourt (Table 3).

Table 3. Percentage change in AADT between 2019 and 2020 by corridor.

Highway	2019–2020 change
Umuahia–Ikot Ekpene	−40.9%
Onitsha–Owerri	−43.3%
Abakaliki–Ogoja	−57.8%
Enugu–Port Harcourt	−48.9%
Owerri–Port Harcourt	−66.3%

The unequal magnitude of the decline provides additional evidence that the highways do not respond identically to region-wide temporal disturbances. The largest reduction occurred on Owerri–Port Harcourt, whereas Umuahia–Ikot Ekpene experienced the smallest decline. This pattern further supports the need to distinguish corridor-specific traffic behaviour rather than interpreting the regional mean as representative of every highway.

3.4 Highway-specific traffic-demand models

3.4.1 Highway-specific regression estimates

Table 4 presents the results of the highway-specific log-linear models.

Table 4. Highway-specific log-linear traffic-demand models.

Highway	R^2	Adjusted R^2	ln GDP	p-value	ln PD	p-value	ln FP	p-value
Abakaliki–Ogoja	0.770	0.727	−0.617	0.651	1.047	0.056	−0.078	0.675
Enugu–Port Harcourt	0.222	0.076	0.621	0.024	0.187	0.462	−0.188	0.515
Onitsha–Owerri	0.227	0.082	0.103	0.785	0.497	0.246	−0.203	0.370
Owerri–Port Harcourt	0.132	−0.031	−0.134	0.915	0.573	0.365	−0.137	0.454
Umuahia–Ikot Ekpene	0.716	0.663	−0.058	0.742	0.790	0.005	−0.261	0.209

PD, passenger population density; FP, fuel price.

The highway-specific models reveal substantial differences in explanatory structure. The Abakaliki–Ogoja model produced an R^2 of 0.770, with passenger population density showing a positive elasticity of 1.047 (p = 0.056), while GDP and fuel price were not statistically significant. The Umuahia–Ikot Ekpene model similarly showed relatively high explanatory power (R^2 = 0.716), with population density having a positive and statistically significant coefficient of 0.790 (p = 0.005).

In contrast, the Enugu–Port Harcourt model had a lower R^2 of 0.222 but displayed a statistically significant GDP elasticity of 0.621 (p = 0.024). This suggests that temporal changes in economic activity were more closely aligned with changes in traffic demand on this highway than on the other highways in the separate models.

The Onitsha–Owerri and Owerri–Port Harcourt models produced comparatively low R^2 values of 0.227 and 0.132, respectively. None of the socioeconomic or fuel-price coefficients was statistically significant in these two models, indicating that the three selected explanatory variables do not adequately capture all of the temporal variation in AADT on these highways.

The differences in model fit are themselves informative. They suggest that traffic demand on some highways is more closely associated with the socioeconomic variables included in the dataset, whereas demand on others may depend more strongly on unobserved characteristics such as freight flows, origin–destination structure, urban accessibility, alternative routes, industrial activity, road condition, travel time and highway-specific land use.

3.5 Formal test of spatially varying demand relationships

3.5.1 Pooled corridor-effects model

A pooled model including corridor effects, GDP, passenger population density and fuel price produced an R^2 of 0.860 and an adjusted R^2 of 0.849. The corresponding model without highway effects had an R^2 of 0.840. The inclusion of highway effects therefore improved model fit, and the joint comparison of the two specifications produced $F = 3.20$, $p = 0.017$.

This result indicates that accounting for the identity of the highway provides additional explanatory information beyond the common socioeconomic variables.

3.5.2 Interaction model

The more important test of spatial heterogeneity was obtained by allowing GDP and population-density coefficients to vary by corridor (Table 5).

Table 5. Corridor-specific elasticities from the pooled interaction model.

Highway	GDP elasticity	p-value	PD elasticity	p-value
Abakaliki–Ogoja	−0.561	0.650	1.162	0.014
Enugu–Port Harcourt	0.621	0.011	0.171	0.094
Onitsha–Owerri	0.071	0.840	0.465	0.099
Owerri–Port Harcourt	−0.030	0.984	0.621	0.182
Umuahia–Ikot Ekpene	−0.091	0.537	0.668	<0.001

PD, passenger population density.

The interaction model produced an R^2 of 0.900 and an adjusted R^2 of 0.883, representing an improvement over the corresponding pooled highway-effects model.

Most importantly, the joint robust Wald test of the eight GDP and population-density interaction terms produced $\chi^2(8) = 34.88$, $p < 0.001$. This provides statistical evidence that the relationships between socioeconomic characteristics and AADT are not constant across the five highways.

Figure 2 presents the estimated highway-specific elasticities of AADT with respect to GDP and passenger population density across the five study highways. The figure illustrates the extent to which changes in economic activity and population concentration are associated with variations in traffic demand on each highway.

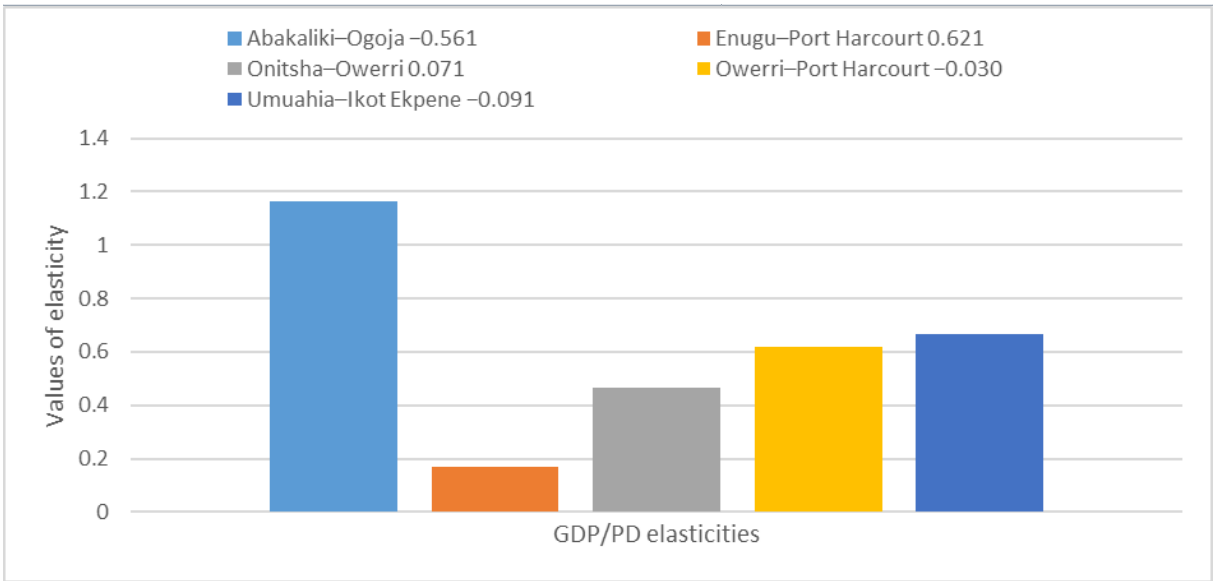


Figure 2. Highway-specific GDP and passenger population-density elasticities.

The results indicate that passenger population-density elasticity is generally stronger than GDP elasticity, suggesting that demographic concentration has a more pronounced association with highway traffic demand across most highways. The Enugu–Port Harcourt highway exhibits comparatively strong elastic responses to both GDP and passenger population density, consistent with its high traffic volume and important commercial and inter-state transport function. Generally, the variation in elasticities across highways demonstrates spatial heterogeneity in the socioeconomic drivers of traffic demand, indicating that highway-specific demographic and economic conditions should be considered in highway planning and traffic-demand forecasting.

4 Discussion

The findings provide evidence that highway traffic demand in South-Eastern Nigeria is strongly differentiated across inter-state corridors. The mean AADT on Enugu–Port Harcourt was 2,202,095 PCU/day, compared with 588,709 PCU/day on Abakaliki–Ogoja. This approximately 3.7-fold difference demonstrates that the regional mean AADT cannot adequately represent the traffic environment of individual corridors.

The large between-highway component of AADT variation is consistent with the wider literature demonstrating that traffic volumes are influenced by road characteristics, socioeconomic conditions, surrounding development and network position. Pulugurtha and Mathew (2021), for example, found that local AADT was related to road density, land use and proximity to higher-order roads, while Sfyridis and Agnolucci (2023) reported that the associations between explanatory variables and traffic volume differed across road classes and vehicle types.

The corridor-specific models provide a particularly important finding. Passenger population density was strongly associated with AADT on Umuahia–Ikot Ekpene and Abakaliki–Ogoja, whereas GDP was the statistically significant socioeconomic variable on Enugu–Port Harcourt. This suggests that different highways may respond to different components of the regional travel market. On one highway, passenger population concentration may be more closely related to traffic generation, whereas on another, commercial and economic activity may provide a stronger explanation.

The passenger population-density elasticity of 1.162 for Abakaliki–Ogoja in the interaction model indicates a comparatively strong association between demographic concentration and traffic demand on that highway. However, the coefficient should not be interpreted as a causal estimate. With only 20 annual observations per highway, the estimate may also reflect omitted temporal factors or measurement relationships.

Similarly, the GDP elasticity of 0.621 for Enugu–Port Harcourt suggests that a 1% increase in GDP was associated with an approximately 0.62% increase in AADT on this highway, conditional on the other variables in the interaction specification. The finding is compatible with transport-demand literature linking economic activity with travel intensity, but the observational design does not establish causality (Chi, 2016; Sfyridis and Agnolucci, 2023).

The significant interaction test is particularly important because it demonstrates that the observed differences are not simply differences in average traffic levels. The coefficients themselves vary across highways. This is consistent with the concept of spatial non-stationarity, whereby the relationship between a dependent variable and explanatory factors changes across geographical settings. Recent spatial AADT research similarly emphasizes that spatial heterogeneity and spatial dependence can influence traffic estimation and model generalization (Ma et al., 2026).

The comparatively weak explanatory power of the Onitsha–Owerri and Owerri–Port Harcourt models indicates that GDP, passenger population density and fuel price alone do not fully describe traffic-demand dynamics on every highway. This finding is not unexpected because inter-state traffic can be affected by factors that are not represented in the current dataset, including freight intensity, industrial location, border or market activity, travel-time reliability, road condition, public transport availability, alternative routes and network centrality.

Fuel price was not statistically significant in any of the five highway-specific models. This should not be interpreted as evidence that fuel prices have no effect on travel demand. Previous research indicates that travel responses to fuel prices may be asymmetric and may differ between short- and long-run adjustments (Chi, 2016). Moreover, fuel price in the present dataset is a common annual variable across the five highways, meaning that it provides only 20 unique annual observations and cannot capture highway-specific differences in fuel-price exposure.

The results also demonstrate the importance of distinguishing spatial heterogeneity from spatial autocorrelation. This study identifies heterogeneity between five predefined highway corridors but does not estimate a continuous spatial process or spatial lag. Consequently, the findings should be interpreted as evidence of highway-level differences rather than as a test of fine-scale spatial autocorrelation. Future research with geocoded traffic-count stations and a larger number of spatial units could employ geographically weighted regression, spatial error/lag models, spatial random effects or spatially informed machine-learning methods.

4.1 Implications for highway planning and management

The findings have several practical implications.

First, traffic planning based solely on a regional average may underestimate demand on high-volume highways and overestimate demand on lower-volume highways. The substantial difference between Enugu–Port Harcourt and Abakaliki–Ogoja illustrates the importance of corridor-specific demand assessment.

Second, infrastructure planning should consider the socioeconomic structure of individual corridors. Where population density is strongly associated with AADT, demographic growth may provide an important indicator for traffic-monitoring expansion and capacity planning. Where GDP is more strongly associated with traffic, economic and commercial activity may be particularly relevant to demand monitoring.

Third, traffic-count programmes can be prioritized using corridor heterogeneity. Highways with high traffic levels and high temporal variability may require more frequent or continuous monitoring, while lower-volume highways can potentially benefit from model-based estimation supplemented by periodic validation counts. This is consistent with broader research showing that traffic estimation can help overcome spatial gaps in direct count coverage (Fu et al., 2017; Mathew and Pulugurtha, 2021).

Fourth, road agencies should avoid applying a single elasticity or traffic-growth assumption to all inter-state highways. The evidence of significant highway-specific interactions indicates that traffic-demand relationships differ spatially and should therefore be incorporated into highway-level planning models.

4.2 Robustness and limitations

Several limitations should be recognized.

First, the study contains only five spatial highways and 100 highway-year observations. Although the dataset provides a balanced longitudinal structure, the small number of highways limits the complexity of spatial models that can be estimated reliably.

Second, the highway-specific regressions contain only 20 observations each. Consequently, individual coefficients may have relatively large standard errors, and statistically insignificant coefficients should not necessarily be interpreted as evidence of no relationship.

Third, some explanatory variables have limited spatial variation. Fuel price is common across highways within a given year, while road length is constant within each highway. This limits the ability to identify highway-specific effects for these variables.

Fourth, the analysis does not include several potentially important determinants of inter-state traffic demand, including freight tonnage, employment density, industrial activity, urban land use, travel-time reliability, road accessibility, vehicle operating costs, public transport supply and origin–destination flows.

Fifth, although the study refers to spatial heterogeneity, it does not constitute a full geographic information-system-based spatial econometric analysis. The five highways are spatial units rather than individual geocoded road links. Therefore, spatial autocorrelation, spatial spillovers and fine-scale local coefficients could not be estimated.

Finally, the 2020 observations represent an unusual disruption in traffic demand. The large reductions observed across all highways may influence the estimated temporal relationships. Future studies should consider longer post-2020 observations and explicitly model structural breaks or major disruptions.

5 Conclusion

This study examined spatial heterogeneity and highway-specific traffic demand relationships across five major inter-state highways in South-Eastern Nigeria using 100 highway-year observations covering 2001–2020. The results demonstrate substantial differences in traffic intensity, with mean AADT ranging from 588,709 PCU/day on Abakaliki–Ogoja to 2,202,095 PCU/day on Enugu–Port Harcourt.

The analysis further demonstrates that spatial differences extend beyond average traffic levels to the relationships between socioeconomic variables and AADT. Passenger population density was particularly important for Umuahia–Ikot Ekpene and Abakaliki–Ogoja, while GDP showed a statistically significant positive association with AADT on Enugu–Port Harcourt. The pooled interaction model confirmed that the relationships between GDP, passenger population density and AADT differed significantly across the five highways, with a robust Wald statistic of 34.88 ($p < 0.001$).

The central contribution of the study is therefore the demonstration that traffic demand in South-Eastern Nigeria is spatially heterogeneous and that a single regional traffic-demand relationship may conceal important highway-specific differences. Highway-specific modelling provides a more informative basis for understanding traffic demand where highways serve different demographic, economic and network functions.

For transport planning, the findings support the use of differentiated highway-level traffic models rather than uniform regional assumptions. Future research should extend the dataset spatially and temporally, incorporate freight, land-use, accessibility and network-connectivity variables, and employ geocoded spatial models capable of distinguishing highway heterogeneity from spatial autocorrelation.

Data availability

The study uses a longitudinal dataset comprising 100 highway-year observations for five inter-state highway pavements in South-Eastern Nigeria covering 2001–2020. The dataset incorporates AADT, socioeconomic, demographic, environmental, fuel-price, vehicle-registration and highway-characteristic variables.

Ethics statement

The study used aggregated secondary traffic, socioeconomic, environmental and highway-level data and did not involve human participants, personal identifiers or individual-level confidential information. Therefore, formal human-subject ethical approval was not required.

Conflict of interest

The author declares that there is no conflict of interest associated with this study.

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Author contributions

The study conception, data analysis, interpretation of results and manuscript preparation were undertaken by the authors.

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