EKOIST Journal of Econometrics and Statistics,
EKOIST 2025, 43: 18–33

https://doi.org/10.26650/ekoist.2025.43.1519393

Submitted 20.07.2024
Revision Requested 04.06.2025
Last Revision Received 03.10.2025
Accepted 01.11.2025

EKOIST Journal of Econometrics and Statistics

Research Article

Open Access

Determinants of Turkish Airport Revenues Using Spatial Panel Regression Models

Arzu Çubukçu [1] & Semra Türkan [1]

[1] Hacettepe University, Department of Statistics, Ankara, Türkiye

Abstract

In this study, the spatial effects of aviation data and economic variables on airport terminal revenues in Türkiye were investigated using spatial panel data models. This study is the first study to model airport revenues in Türkiye spatially. Based on previous studies, the variables that are thought to affect terminal revenues were as follows: number of passengers, cargo volume, annual exchange rate, real gross domestic product (GDP), and number of foreign visitors. Four different spatial panel data models were applied in the analysis: Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Autoregressive Combined Model (SAC) and Spatial Durbin Model (SDM). Statistical tests and model fit criteria were used to determine the most appropriate model. The Hausman test was performed to decide between fixed and random effects, and the Akaike information criterion (AIC) and Bayesian information criterion (BIC) were evaluated to compare model performances. Because of the Hausman test, fixed-effects models were more appropriate than random-effects models. Among the fixed effects models, the SDM model was determined to be the best fit according to the AIC and BIC values. According to the findings of the SDM model, the number of passengers had a statistically significant and positive effect on terminal revenues, and the number of foreign visitors in neighbouring cities had a statistically significant but negative effect on terminal revenues.

Keywords Aviation Data · Spatial Panel Models · Moran's I · Hausman Test

Citation: Çubukçu, A. & Türkan, S. (2025). Determinants of Turkish airport revenues using spatial panel regression models. *EKOIST Journal of Econometrics and Statistics*, 43, 18-33. https://doi.org/10.26650/ekoist.2025.43.1519393

Corresponding author: Semra Türkan sturkan@hacettepe.edu.tr

Determinants of Turkish Airport Revenues Using Spatial Panel Regression Models

The common goal of all countries is to achieve economic growth, increase industrial and trade volumes, and reduce poverty. Cooperation between countries, the development of mutual trade relations, and cultural interactions play a critical role in achieving these goals. The transportation sector is one of the most important tools that support and facilitate such relations. In particular, air transportation strengthens economic and social ties between countries by enabling the rapid, safe, and efficient movement of people, goods, and services on a global scale. The aviation sector plays a strategic role in international trade development, tourism activity expansion, and foreign investment opportunities. Thanks to this sector, geographical distances have lost their meaning and it has become possible to establish closer economic and cultural interactions between countries. Air transportation supports a more inclusive development process by integrating not only major cities but also regional centres into the global network.

The development of aviation in Türkiye has made significant progress in the historical process. The first commercial domestic flights started in 1933 on the Istanbul-Eskişehir-Ankara route, and the first international flight on the Ankara-Istanbul-Athens line in 1947 followed. Over time, the number of passengers on domestic and international flights in Türkiye has significantly increased, and demand has tended to increase continuously, especially during periods of economic stability. The increase in the number of international flights, the increase in foreign tourism and business travel due to globalisation, and the entry of low-cost airlines into the market have been the main factors supporting this growth (Efendigil and Eminler, 2017).

Today, airports are seen not only as transportation points but also as important tools for economic and regional development. The quality of the services provided by airports, infrastructure investments, logistics facilities, and connected land/air transportation networks directly affect the economic development of the regions where they are located. In this context, the spatial effects of airports are becoming increasingly important. The locational advantages of airports in different regions create economic interactions and externalities on the surrounding provinces and regions. Therefore, in the comparative assessment and development of airports, not only operational efficiency but also spatial context should be considered. Airports' accessibility and their interactions with the industrial, tourism, and service infrastructure in their immediate vicinity should be considered together with regional planning and transportation policies. Thus, the aviation sector can be evaluated with a more holistic approach as a fundamental component of national development strategies. In the aviation sector, as in many other sectors, it is of great importance to know how to read, analyse and predict how data can be used in the future. Aviation authorities and operators consider demand forecasts and simulations valuable to determine potential demand in terms of passengers and traffic or to eliminate capacity deficiencies. In evaluating potential demand, socioeconomic indicators at the country or city level are as critical as past passenger data.

Airport terminal revenues are assumed to be determined by the demand for air transport and the accessibility conditions provided by transportation. As the number of passengers and cargo volume increase, airports' services are expected to increase. With faster transportation and shorter travel times, air travel increases, which is expected to have a positive effect on revenues. As income level and the volume of economic activity grow, travel and service use also increase. Changes in the exchange rate and the movements of foreign visitors affect tourism and business travel, which are reflected in terminal revenues. Because of the closeness and interactions between provinces, mobility in one province may increase revenues in neighbouring provinces or reduce them by attracting demand to itself. For these reasons, it is considered appropriate to explain terminal revenues by taking into account both the indicators within the province and the effects coming from neighbouring provinces.

The relationship between aviation sector data and economic variables was examined and modelled for the period 2013-2023. In this context, the relationship between terminal real revenues and airport passenger numbers, cargo volume (tons), annual exchange rate (real effective exchange rate for developing countries), tourist arrivals (distribution of foreign visitors according to the provinces of entry into Türkiye), and real gross domestic product (GDP) was analysed using spatial models. Real terminal revenues and real GDP were used in the analyses to remove the effects of regional inflation. This is the first study in Türkiye to analyse aviation sector revenue data with spatial panel data models. In this way, the determinants of terminal revenues were tested under the same framework by considering both local indicators and the interactions with neighbouring provinces, and a reproducible and comparable set of findings was provided to the literature in the context of Türkiye.

The second section of the study briefly introduces spatial panel data models. The variables used in the study were discussed and explained in detail in the next section. The existence of spatial effects was first investigated in the analysis section, and then the estimates of spatial panel data models were made. In model selection, criteria such as AIC and BIC were evaluated with the results of the Hausman and LM tests. In the last section, the findings were discussed and general evaluations were made.

Literature Review

When the studies conducted on airport data in recent years are examined, the studies on determining the variables affecting the number of passengers are generally more prevalent. The literature on the studies conducted on airport data in recent years is given below:

Daraban and Fournier (2008) examined the impact of low-cost carriers and their spatial dependencies with neighbouring airline routes in the US using spatial panel data econometrics techniques. Chen et al. (2015) investigated the regional effects of infrastructure (roads, railways, transit, and airports) in the Northeastern US, modelling the data with fixed effects spatial panel data models to account for spatial dependencies. Tesfay (2016) analysed load factor trends for North Atlantic (NA) and Middle Atlantic (MA) flights for the European Airlines Association using data from 1991 to 2013 and applied spectral density forecasts and dynamic time effects panel data regression models. Chen et al. (2017) analysed the cost functions of airports in China from 2002 to 2012, identifying the spatial factors that explain the distribution of airports and the conditions needed to enhance cost efficiency. Albayrak et al. (2020) and his colleagues analysed the factors affecting passenger air traffic. They showed that GDP per capita, population, distance to alternative airports, tourism, and number of foreign residents had effects on air passenger traffic between 2004 and 2014. They used fixed- and random-effects panel data models. Erdem et al. (2020) analysed the topology of the Turkish air transportation networks. Because of the analysis, air transportation network flows showed that the western part of Türkiye is more connected than the eastern part. They concluded that the main airports indicated by proximity are Istanbul, Ankara, Izmir, and Antalya.

King-Yin et al. (2020) used a dynamic spatial panel regression model to examine which variables affect airport capacity in a multi-airport region. The results of the model show that airport degree, flight frequency, airport capacity utilisation, income, population, GDP, and fuel price are important factors affecting airport capacity. Karanki et al. (2020) used US airport data for the period 2009 –2016 and examined the factors determining the airports' aviation-related fees and the spatial dependence between neighbouring airports using a spatial panel regression model. The analysis showed a positive spatial dependence between neighbouring airports, that is, the pricing decisions of an airport are affected by the decisions of neighbouring airports.

In addition, aviation activities are subsidised by nonaviation revenues. Marinos et al. (2022) examined the effects of gross domestic product, private sector net capital stock, employment and transportation infrastructure net capital stock variables on gross output in Greek regions for the period 2000-2013 with the dynamic Durbin spatial model. According to the model result, they concluded that the direct effect of highway capital stock is higher than that of airports and ports. In general, the total effect of transportation capital stock remains below its indirect effects when separated by transportation type. Tirtha et al. (2023) examined airline passenger arrivals and departures for 510 airports in the United States for five years using a common panel generalised ordered probit model system with observed thresholds. According to the model results, the main factors affecting airline demand are metropolitan statistical area (MSA) population, median income, education level, airport location, and temporal factors.

In their study, Lenaerts et al. (2023) examined aviation sector data at the European NUTS-3 level using a spatial-econometric approach with instrumental variables. According to the model results, there were increases in service sector employment due to improved air transportation access in regions close to the airport. In addition, the average total effect of connectivity increases on service employment was positive. Fan et al. (2024) examined aviation data from 35 large and medium-sized cities in China between 2003 and 2017 using the multi-scale geographical and temporal weighted regression (MGTWR) model. As a result of the model, they concluded that there is a positive relationship between the number of passengers carried by air and innovation performance in the high-tech industry, and that the effects in Southwest China are higher than in other regions of the country. Türkan (2024) examined regional factors affecting airline passenger demand, aircraft demand, and cargo volume on a provincial basis in Türkiye with penalized geographically weighted regression models. The study found that the export—an indicator of regional economic growth—is the most influential determinant of passenger demand, aircraft demand, and cargo volume. Yang et al. (2025) examined data from 31 provinces in China, excluding Hong Kong, Macau, and Taiwan, for the period 2004–2019. The supply and demand levels in civil aviation passenger transportation were investigated using the entropy-weighted TOPSIS method. In addition, the authors examined the factors affecting the development between supply and demand in the aviation sector using the double fixed-effect model. According to the results, the supply-demand matching and compatibility level at the provincial level increased to the upper-medium level, and significant spatial differences were observed. Economic development, urbanisation, and openness were found to have a significant—and positive—impact on supply–demand development. Ergün (2025) analysed data on passenger traffic, cargo traffic, and aircraft movements at Turkish airports. The results of the study reveal that larger, economically active cities tend to have higher aircraft movement levels due to the dual effects of business and population density.

These studies demonstrate the importance and usefulness of spatial econometric models in understanding the interactions of various factors in the aviation sector. The spatial studies conducted on the aviation sector mentioned above are summarised in the table below:

Table 1

Researchers	Subject	Model/Method Used	Main Findings
Chen et al. (2015)	Regional impact of infrastructure in Northeastern United States	Fixed-Effects Spatial Panel Data Model	Successfully modelled the spatial dependencies and effects of regional infrastructure.
	Load factor trends for European Airlines' North Atlantic and Middle Atlantic flights		
	Association	Dynamic time effects of the panel data regression models	Explained the seasonal and temporal variations in load factor trends.

Researchers	Subject	Model/Method Used	Main Findings
Tesfay (2016)			
Chen et al. (2017)	Analysis of the cost function of airports in China	Spatial econometric models	Spatial factors must be considered to enhance airport cost efficiency in China.
Albayrak et al. (2020)	Factors affecting air passenger traffic in Türkiye	Fixed- and random-effects panel data models were used.	The GDP per capita, population, distance to alternative airports, tourism, and number of foreign residents affected passenger air traffic.
Erdem et al. (2020)	Topology analysis of Turkish air transportation networks	Network analysis	The flow of the air transportation network showed that the western part of Türkiye is more connected than the eastern part.
King-Yin et al. (2020)	Determining the variables that affect airport capacity in a multi-airport region	The dynamic spatial panel regression model	Airport degree, flight frequency, airport capacity utilisation, income, population, GDP, and fuel price are important factors affecting airport capacity.
Karanki et al. (2020)	Analysis of the factors determining airports' aviation-related fees	The spatial panel regression model	Positive spatial dependence between neighbouring airports
Marino et al. (2022)	Analysis of the effects of gross domestic product, private sector net capital stock, employment, and transportation infrastructure net capital stock variables on gross output in Greece	Dynamic Durbin spatial model	The total effect of transportation capital stock remains below its indirect effects when transportation type is separated
Tirtha et al. (2023)	Examining the quarterly airline passenger arrivals and departures for 510 U.S. airports	Common panel generalized ordered probit model system with observed thresholds is presented.	The main factors affecting airline demand are metropolitan statistical area (MSA) population, median income, education level, airport location, and temporal factors.
Lenaerts et al. (2023)	Analysis of Aviation Sector Data at the European NUTS-3 Level	Spatial-econometric approach using instrumental variables	Service sector employment increased due to improved air transportation access in regions close to the airport.
Fan et al. (2024)	Analysis of panel data on aviation from 35 large and medium-sized cities in China	Multiscale geographical and temporal weighted regression model	A positive relationship exists between the number of passengers carried by air and innovation performance in the high-tech industry.
Türkan (2024)	Regional factors affecting airline passenger demand, aircraft demand, and cargo volume in Turkey	Penalized geographically weighted regression models	The most important factor affecting passenger demand, aircraft demand, and cargo volume is exports.
Yang et al. (2025)	Analysis of data from 31 provinces in China, excluding Hong Kong, Macau, and Taiwan	The entropy-weighted TOPSIS method, double fixed-effect model	The supply-demand matching and compatibility level at the provincial level increased to the upper-medium level.
Ergün (2025)	Analysis of passenger traffic, cargo traffic, and aircraft movements at Turkish airports	Correlation and Trend Analysis	Larger, economically active cities tend to have higher levels of aircraft movement due to the dual effects of business and population density

Data Description

Data were obtained from the State Airports Authority, Turkish Statistical Institute, and the Central Bank of the Republic of Türkiye. In this study, the data of 48 airports in Türkiye between 2013 and 2023 were analysed with spatial panel regression models using the "splm", "spdep" and "SDPDmod" packages in the R programme. In the spatial panel regression models, passenger numbers, cargo volume (tons), real effective exchange rate based on developing countries, tourist arrivals, and real GDP variables were included as independent variables, and terminal real revenues were included as dependent variables. The 48 airports examined in the study are listed in Table 1:

Table 2

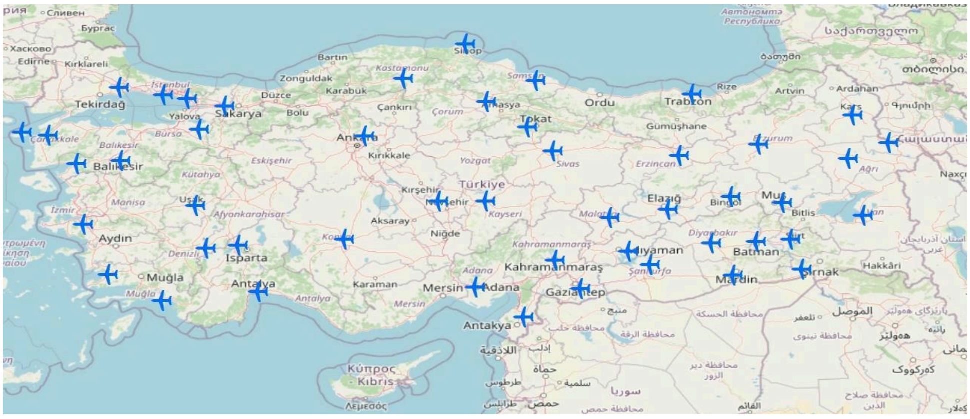
List of airports used in the study

Adana Airport	İzmir Adnan Menderes Airport
Adıyaman Airport	Kahramanmaraş Airport
Ağrı Ahmed-i Hani Airport	Kars Harakani Airport
Amasya Merzifon Airport	Kastamonu Airport
Ankara Esenboğa Airport	Kayseri Airport
Antalya Airport	Kocaeli Cengiz Topel Airport
Balıkesir Koca Seyit Airport	Konya Airport
Balıkesir Merkez Airport	Malatya Airport
Batman Airport	Mardin Airport
Bingöl Airport	Muğla Dalaman Airport
Bursa Yenişehir Airport	Muğla Milas-Bodrum Airport
Çanakkale Airport	Muş Sultan Alparslan Airport
Çanakkale Gökçeada Airport	Nevşehir Kapadokya Airport
Denizli Çardak Airport	Samsun Çarşamba Airport
Diyarbakır Airport	Siirt Airport
Elazığ Airport	Sinop Airport
Erzincan Airport	Sivas Nuri Demirağ Airport
Erzurum Airport	Şanlıurfa GAP Airport
Gaziantep Airport	Şırnak Şerafettin Elçi Airport
Hatay Airport	Tekirdağ Çorlu Airport
Iğdır Şehit Bülent Aydın Airport	Tokat Airport
Isparta Süleyman Demirel Airport	Trabzon Airport
Istanbul Atatürk Airport	Uşak Airport
Istanbul Sabiha Gökçen Airport	Van Ferit Melen Airport

A map of Turkey's civil aviation airports was obtained, as shown in Figure 1:

Figure 1

Civil Air Traffic Airports in Turkey



The variables used in the analysis, variable abbreviations, and the institutions from which the data on the variables were obtained are given in Table 2:

Table 3

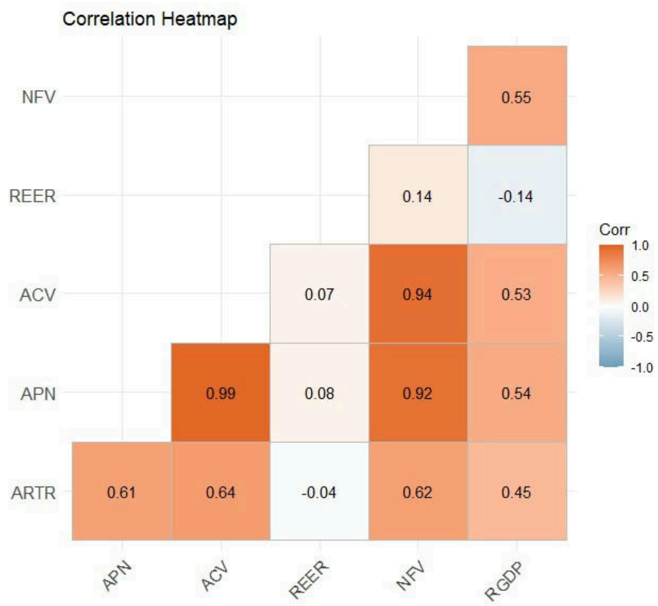
Variables and Abbreviations

Variables	Variable Abbreviations	Data Source
Airport Real Terminal Revenue (TL)	ARTR	DHMI
Number of Airport Passenger (Person)	APN	DHMI
Airport cargo volume (ton)	ACV	DHMI
Real Effective Exchange Rate Based on Developing Countries	REER	TCMB
Number of Foreign Visitors to Turkey	NFV	TCMB
Real Gross Domestic Product (GDP) Value (Based on 2009)	RGDP	TURKSTAT

Figure 2 shows the correlation heatmap for the variables used in the study:

Figure 2

Correlation Heatmap



The correlation heatmap in Figure 2 is examined, it is seen that there is a very strong and powerful relationship of 0.99 between ACV and APN and 0.94 between ACV and NFV. Therefore, ACV should not be included in the analysis. This variable was removed from the study.

Since the measurement units of the indicators are different, the natural logarithm of the indicators was taken. Table 3 provides descriptive statistics for the variables used in the study:

Table 4

Descriptive Statistics

Variables	Mean	Std. Error.	Median	Min.	Max.
ln_ARTR	45824	0.11	15.92	0.00	22.88
ln_APN	28460	0.12	35400	0.00	17.42
ln_REER	43191	0.01	42461	28185	42125
ln_NFV	33725	0.18	22798	0.00	14.18
ln_RGDP	17.30	0.06	45978	14.70	22.81

Methodology

In this section, we briefly explain basic information about the spatial panel data models used in the study.

Spatial Panel Data Models

The general linear panel regression model is written as follows:

$$y_{\mathrm{it}} = \beta_{0\mathrm{it}} + \sum_{k}^{K} = 1\beta_{\mathrm{kit}}x_{\mathrm{kit}} + u_{\mathrm{it}}$$
$$, i = 1, ..., N; t = 1, ..., T \tag{1}$$

where N is the number of cross-sectional units, T is the number of time periods (usually N>T), yit is the value of the dependent variable for unit i at time t, xkit is the value of the k independent variables for unit i at time t, β0it is intercept term for unit i, βkit is the coefficient of the k*th* explanatory variable for unit i at time t, and uit is the error term.

In the panel data model in (1), the error component is typically expressed as in (2):

$$u_{\mathrm{it}} = \mu_{\mathrm{i}} + v_{\mathrm{it}} \tag{2}$$

In (2), μi represents the unobserved unit-specific effect, and, vit indicates the residuals (Baltagi, 2005). uit denotes normally distributed errors with zero mean and constant which are identical and independent across all times and units (Tatoğlu, 2018).

In the spatial model developed by Manski (1993), which is the most general among spatial models, the matrix representation is as shown in (3), where I_T, is a unit matrix of size T, W_N, is an NxN weight matrix, and W = IT ⊗ W :

$$y = \rho \mathrm{Wy} + \mathrm{X}\beta + \mathrm{WX}\theta + \mathrm{u}, \mathrm{u} = \lambda \mathrm{Wu} + \varepsilon \tag{3}$$

The spatial lag term, denoted by Wy, represents the weighted average of y in neighbouring regions. The behaviour of neighbouring regions is interdependent. ε denotes the spatial autocorrelation between residuals of neighbouring regions. ρ is called the spatial autoregressive coefficient, λ represents the spatial autocorrelation coefficient. Both coefficients measure the strength of the inter-unit dependence (Tatoğlu, 2022).

Spatial Autoregressive Model (Spatial Lag Model) (SAR)

Spatial dependence can be expressed through Tobler's first law, which states that "everything is related to everything else, but near things are more related than distant things." In short, spatial dependence refers to the influence of other locations within the model on the location under study. The spatial dependence is determined using the spatial lag (autoregressive) model. The spatial lag term, Wy, is added to the spatial lag model (Gülel, 2013). The SAR is expressed as Equation (4):

$$\begin{gathered} \mathrm{y} = \rho\mathrm{Wy} + \mathrm{X}\beta + \mathrm{u} \\ (\mathrm{I} - \rho\mathrm{W})\mathrm{y} = \mathrm{X}\beta + \mathrm{u} \\ y = (\mathrm{I} - \rho\mathrm{W})^{-1}\mathrm{X}\beta + (\mathrm{I} - \rho\mathrm{W})^{-1}u = (\mathrm{I} - \rho\mathrm{W})^{-1}\,(\mathrm{X}\beta + u) \end{gathered} \tag{4}$$

In (4), y is an Nx1 dependent variable vector, W is an NxN spatial weight matrix, ρ is the spatial lag parameter, and X is an N×K observation matrix. The spatial lag term Wy and the error term u are always related in the model. Additionally, the lag term at location i is correlated with the error terms in all locations. This situation leads to the use of inconsistent estimators in the ordinary least squares (OLS) estimation.

SAR can be rewritten as

$$y = \rho\mathrm{Wy} + \varepsilon, \varepsilon \sim N(0, \sigma^2 I_n) \tag{5}$$

The OLS estimate of ρ in (5) is obtained as shown in (6)

$$\hat{\rho} = (y'W'\mathrm{Wy})^{-1}\, y'W'y \tag{6}$$

However, the OLS estimator for ρ in (6) is biased. When estimating autoregressive parameters, the ML method can be used instead of OLS (Şentürk, 2019).

Spatial Error Model (SEM)

SEM examines the spatial dependence among error terms of neighbouring regions. This is because if a spatial relationship exists among independent variables that are not included in the model, their effects manifest as error terms. This situation leads to spatial dependence (Tatoğlu, 2022). SEM is expressed as Equation (7):

$$y = \mathrm{X}\beta + u; u = \lambda\mathrm{Wu} + \varepsilon \tag{7}$$

Spatial Autoregressive Mixed Model (SAC or SARAR)

Kelejian and Prucha (1998) introduced the SAC model, which is similar in many aspects to the SAR model (Golgher and Voss 2015; Bivand et al. 2021). SAC is expressed as Equation (8):

$$y = \rho\mathrm{Wy} + \mathrm{X}\beta + u; u = \lambda\mathrm{Wu} + \varepsilon \tag{8}$$

Spatial Durbin Model (SDM)

The SDM is the stripped-down version of the spatial autoregressive model (SAR model) in which spatially autocorrelated error terms (ρ≠ 0) are removed. Spatial effects are incorporated in both the dependent and independent variables. SDM is expressed as Equation (9):

$$y = \rho\mathrm{Wy} + \mathrm{X}\beta + \mathrm{WX}\theta + u \tag{9}$$

(Tatoğlu, 2022).

Spatial Panel Data Models

Spatial panel data consist of observations over time for spatial units (such as countries, regions, and states). While panel data models reveal variability among cross-sectional units, spatial panel data models also address spatial correlation.

The spatial classic panel data model is expressed as follows:

$$\mathrm{yi}_t = \mathrm{xi}_t{}'\beta + \varepsilon_{\mathrm{it}}, i = 1, ..., N; t = 1, ..., T \tag{10}$$

The matrix-vector representation of the classic model in (10) is as follows:

$$y_t = X_{\mathrm{t}}\beta + \varepsilon_t \tag{11}$$

where yt is vector of cross-sectional data for time t with Nx1, Xt is matrix of cross-sectional independent variables for time t

with NxK, εt is vector of error terms for time t with Nx1.

Spatial effects can be examined as fixed effects and random effects in panel data analysis, disregarding the spatial weight matrix

(W). However, in this case, while the presence of spatial effects can be acknowledged, whether this effect originates from neighbours or from the error term cannot be determined. The structure of spatial dependence is examined under the spatial lag and spatial error models in fixed and random effects models (Güriş, 2015).

Fixed-effect SAR, SEM, SAC, and SDM Models

When unobserved variables associated with independent variables are added to the model, the fixed effects panel data model is expanded for spatial lag and error models (Güriş, 2015). The fixed-effect SAR is expressed as Equation (12):

$$\begin{gathered} y_t = \mathrm{\rho W y}_t + X_t\beta + \mu + \mathrm{\varepsilon t}, \\ E(\mathrm{\varepsilon t}) = 0, E(\mathrm{\varepsilon t}\ \mathrm{\varepsilon t}\ ') = \sigma^2 I \end{gathered} \tag{12}$$

where ρ spatial autoregressive coefficient. The fixed-effect SEM is expressed as Equation (13):

$$y_t = X_t\beta + \mu + \varphi_t \tag{13}$$

where φt = λWε*(t)* +ε(t) .

The fixed effects SAC is expressed as Equation (14):

$$y_t = \mathrm{\rho W y}_t + X_t\beta + \mu + \varphi_t \tag{14}$$

where φ_t = $\lambda \mathrm{W} \varepsilon_t \sim + \varepsilon_t$.

The fixed effects SDM model is described follows:

$$y_t = \mathrm{\rho W}\ y_t + X_t \sim \beta + W X_t \sim \theta + \varepsilon_{\mathrm{t}} \tag{15}$$

Random-effect SAR, SEM, SAC, and SDM Models

Another way to incorporate unobserved effects into the model is through the use of random effects models. These unobserved effects are treated as the model's error term and are not associated with the independent variables. In cases where there are spatial effects in cross-sectional units, the random effects spatial SAR is expressed as Equation (16):

The random effect spatial SEM is

$$y_t = \mathrm{\rho WN}\ y_t + X_t\beta + \varepsilon_{\mathrm{t}} = \alpha + u_{\mathrm{t}} \tag{16}$$

where $\varepsilon = \alpha + B^{-1}u$

and $B = (I_N - \lambda W)$.

$$y_t = X_t\beta + \varepsilon_t \tag{17}$$

The random effect spatial SAC is expressed as Equation (18):

$$y_t = \rho W\ y_t + X_t\beta + \alpha + \varphi_t(18) \tag{18}$$

where α represents the random effect.

The random effects spatial SDM is expressed as Equation (19):

$$y_t = \rho WN\ y_t + X_t\beta + WX_t\theta + \varepsilon_t, \varepsilon_t = \alpha + u_t \tag{19}$$

Results

Before estimating the models, the existence of spatial dependence is investigated using Moran's (1950) global Moran's-I tests. The Moran I statistic measures the dependency or correlation between an observation and its neighbours. The Moran's-I test value is not a correlation coefficient because it does not range between −1 and +1. Although it is one of the most widely used tests, it is difficult to interpret. This is because while the null hypothesis "H_0: λ = 0" assumes no spatial dependency, the alternative hypothesis lacks a clear statement. If the resulting coefficient is insignificant, it indicates that neighbours do not affect each other, meaning that space is not important. If the resulting coefficient is significant, it indicates a spatial interaction. Table 4 shows the results of global Moran's I test for each year and variable.

Table 5

Global Moran's I test results

	Moran's I (p-value)				
Year	**ARTR**	**APN**	**REER**	**RGDP**	**NFV**
2013	0.0609 (0.0000)*	0.1140 (0.0000)*	−0.0207 (0.3424)	0.0828 (0.000)*	0.1007 (0.000)*
2014	0.0666 (0.0000)*	0.1148 (0.0000)*	−0.0207 (0.3424)	0.0841 (0.000)*	0.0974 (0.0001)*
2015	0.0935 (0.0000)*	0.1137 (0.0000)*	−0.0207 (0.3424)	0.0806 (0.000)*	0.0952 (0.0001)*
2016	0.1151 (0.0000)*	0.0957 (0.0001)*	−0.0207 (0.3424)	0.0797 (0.000)*	0.0810 (0.0002)*
2017	0.1108 (0.0000)*	0.1035 (0.0001)*	−0.0207 (0.3424)	0.0805 (0.000)*	0.0821 (0.0003)*
2018	0.1080 (0.0000)*	0.1077 (0.0000)*	−0.0207 (0.3424)	0.0841 (0.000)*	0.0867 (0.0002)*
2019	0.0955 (0.0000)*	0.1056 (0.0000)*	−0.0207 (0.3424)	0.0875 (0.000)*	0.0889 (0.0001)*
2020	0.0840 (0.0000)*	0.0750 (0.0005)*	−0.0207 (0.3424)	0.0835 (0.000)*	0.0693 (0.0005)*
2021	0.0991 (0.0000)*	0.0879 (0.0002)*	−0.0207 (0.3424)	0.0905 (0.000)*	0.0680 (0.0010)*
2022	0.0992 (0.0000)*	0.0977 (0.0001)*	−0.0207 (0.3424)	0.0932 (0.000)*	0.0846 (0.0002)*
2023	0.1039 (0.0000)*	0.0960 (0.0001)*	−0.0207 (0.3424)	0.0903 (0.000)*	0.0850 (0.0002)*

*Significant level 0.05

When Table 4 is examined, it is seen that the spatial effect is statistically significant for all variables in all years except the REER variable. This is because the REER variable is calculated at the country level and does not differ between cities in the same year; therefore, it was excluded from the spatial analysis.

A weight matrix that reflects spatial dependency must be created before obtaining estimates for spatial models. In this study, a distance-based method was used to create the weight matrix, and a distance weight matrix based on geographical distances between cities was used. Figure 3 illustrates the construction of the weight matrix based on the Euclidean distance definition on the map of Turkey. According to this, for Adana Airport with an ID of 1, which is closer to itself than the distance threshold (192877.5481 m), it takes the value of 0.5 in the weight matrix, whereas for Hatay Airport with an ID of 20, it also takes the value of 0.5 in the weight matrix. Adana Airport is not affected by Gaziantep Airport with an ID of 18, which is farther away from it than the distance threshold (192877.5481 m). The straight-line distance between these airports is expressed as follows:

The distance between Adana Airport and Hatay Airport is 113.38 km (113380 m).

The distance between Adana Airport and Kahramanmaraş Airport is 160.34 km (160340 m). The distance between Adana Airport and Gaziantep Airport is 195.41 km (195410 m).

Figure 3

Representation of Airport-Related Weightings

After creating the weight matrix, the fixed and random effects SAR, SEM, and SAC spatial panel data models were estimated using “splm” package in R programme. The “splm” package does not support the SDM model, and the “SDPDmod” package only allows for fixed-effects estimation. Thus, the SDM model was estimated solely with fixed effects using the “SDPDmod” package. R programme was chosen for the analysis because it does not require a software licence. The Hausman test was applied to decide whether the model should have a fixed effect or random effect. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were also evaluated together to compare different model specifications. Both methods were considered together, and the most appropriate model was decided.

The relationship between the real income variable of airports and other independent variables is generally expressed using Equation (20):

$ln\_ARTRit = \beta 0 + \beta 1\ ln\_APNit + \beta 2\ ln\_GDPit + \beta 4\ ln\_NFVit + uit$ (20)

The estimation results for the spatial panel regression model are presented in Table 5, and the results for the Hausman test are presented in Table 6

Table 6

Global Moran’s I test results

	SAR_FE	SAR_RE	SEM_FE	SEM_RE	SAC_FE	SAC_RE	SDM_FE
ln_APN	0.5133 (0.0000)*	0.5334 (0.0000)*	0.5186 (0.0000)*	0.5268 (0.0000)*	0.4969 (0.0000)*	0.5344 (0.0000)*	0.5225 (0.0000)*
ln_RGDP	0.7694 (0.0000)*	0.5909 (0.0000)*	0.9453 (0.0000)*	0.7521 (0.0000)*	1.7769 (0.0008)*	0.6016 (0.0000)*	1.0178 (0.1655)
ln_NFV	0.0928 (0.0351)*	0.0388 (0.1203)	0.1110 (0.0115)*	0.0341 (0.1974)	0.1222 (0.0037)*	0.0390 (0.1205)	0.1146 (0.0093)*
W*ln_APN	-	-	-	-	-	-	−0.1360 (0.2178)

	SAR_FE	SAR_RE	SEM_FE	SEM_RE	SAC_FE	SAC_RE	SDM_FE
W*ln_RDGP	-	-	-	-	-	-	−0.2559 (0.7316)
W*ln_NFV	-	-	-	-	-	-	−0.3412 (0.0337)*
Constant	-	−6.0110 (0.0000)*	-	−3.8842 (0.0011)*	-	−5.8475 (0.0000)*	-
rho	0.1771(0.0462)*	0.2982 (0.0000)*		-	−0.8639 (0.0012)*	0.2757 (0.0049)*	0.2691 (0.0101)*
phi	-	0.3711 (0.0001)*	-	0.4319 (0.0005)*	-	0.3731 (0.0005)*	-
lambda	-	-	0.3012 (0.0029)*	0.3772 (0.0011)*	0.6889 (0.0000)*	0.0662 (0.6888)	-
LM	4.3543 (0.0369)*		12.9191 (0.0003)*				
Robust LM	1.2561 (0.2639)		9.8209 (0.0017)*				
AIC	1426.99	3068.49	1431.79	1669.59	1525.86	2996.47	1420.791
BIC	1452.35	3093.85	1457.15	1694.95	1559.68	3026.06	1450.376

*Significant level 0.05

Table 7

Results of the Hausman Test

SAR	SEM	SAC	
Hausman test statistics	16.026	78.077	24.954
p-value	0.001*	0.000*	0.000*

*Significant level 0.05

The Hausman test, LM/Robust LM diagnostics, and information criteria (AIC/BIC) were used together in the model selection process. As shown in Table 6, the p-values for SAR, SEM, and SAC are below 0.05, so fixed effects are preferred over random effects. The LM results show spatial dependence; for the SAR_FE (Lag model), the LM test is significant ($p = 0.0369$), but the robust LM is not ($p = 0.2639$). This means that the lag effect is not strongly supported. For the SEM_FE (Error model), both the LM test ($p = 0.0003$) and the robust LM test ($p = 0.0017$) are significant. This shows that the SEM_FE is supported. Therefore, when both LM and robust LM results are considered, the SEM_FE model should be preferred according to the LM test. However, more general models (SAC and SDM) were also estimated and compared with AIC/BIC. As shown in Table 5, SDM_FE has the lowest AIC (1420.791) and BIC (1450.376), so SDM_FE is the most suitable model overall (with SAR_FE reported as a strong alternative for robustness).

In the SDM_FE model, the passenger variable (ln_APN) is statistically significant at the 1% level, with a coefficient of 0.5225, implying that a 1% increase in passengers raises terminal revenues by approximately 0.52%. The number of foreign visitors (ln_NFV) is positive and significant (0.1146, $p<0.01$), whereas ln_RGDP is not statistically significant. The spatial lag of foreign visitors (W·ln_NFV) is negative and significant (−0.3412, $p<0.05$), indicating that there are adverse spillovers from neighbouring regions. The spatial dependence parameter is also significant ($\rho = 0.0101<0.05$), confirming that revenues in one city are influenced by those in neighbouring cities.

SDM_FE provides the most comprehensive and appropriate explanation of terminal revenues by capturing both direct effects and spatial spillovers. Therefore, it was selected as the most suitable model for the analysis.

Conclusion

The general results, based on SDM_FE, show that an increase in air travel demand has a significant and positive effect on terminal revenues. This effect is consistent with the fact that non-aviation revenues, such as retail, food and beverage, and parking inside the terminal, are highly sensitive to passenger traffic in addition to ticket sales. The findings indicate that the number of foreign visitors has a positive local effect, but an increase in foreign visitors in neighbouring provinces leads to negative spatial spillovers in terminal revenues. Although the direct effect of real GDP is unclear, the significance of the ρ parameter confirms the presence of neighbourhood effects in terminal revenues. Therefore, passenger volume and spatial interactions can be considered the main determinants of terminal revenues.

Based on these results, policy recommendations highlight that passenger-focused strategies are the most important for increasing terminal revenues. Rearranging the mix of products and services inside the terminal (e.g., shops, food and beverage options, fast payment systems, and rest areas), improving the passenger experience (e.g., guidance, shorter waiting times, and digital information screens), and applying dynamic pricing can increase passenger spending. Selective reductions in ground service fees, incentives for low-cost carriers, and improvements in transfer quality can strengthen passenger flows on routes with high demand potential. In addition, improving transport connections between the airport, city centre, and tourist areas, as well as introducing multi-modal tickets, can make travel easier and more attractive. Coordinating tourism and event schedules with neighbouring provinces and developing regional tour packages can reduce negative spatial effects, while revenue sharing or joint incentive systems can prevent destructive competition and increase total demand. Strengthening cold chain infrastructure, speeding up customs procedures, and special planning for e-commerce shipments can diversify terminal revenues. Spreading demand during peak hours, efficient planning of counters, gates, and security resources, and biometric/self-service solutions can reduce processing times, increasing passenger satisfaction and spending opportunities. Finally, scenario analysis and flexible contract/insurance mechanisms can provide resilience against unexpected shocks such as pandemics, currency fluctuations, and geopolitical risks. Overall, these policy recommendations show that strategies that expand passenger volume and strengthen regional coordination can sustainably increase terminal revenues.

Peer Review: Externally peer-reviewed.
Author Contributions: Conception/Design of study: S.T; Data Acquisition: A.Ç; Data Analysis/Interpretation: A.Ç.; Drafting Manuscript: A.Ç., F.K; Critical Revision of Manuscript: A.Ç; Final Approval and Accountability: A.Ç., S.T.
Conflict of Interest: The authors have no conflict of interest to declare.
Grant Support: The authors declared that this study has received no financial support.

Author Details

Arzu Çubukçu
[1] Hacettepe University, Department of Statistics, Ankara, Türkiye
0000-0002-0744-4056 arzu.cbkc2@gmail.com

Semra Türkan (Prof.Dr.)
[1] Hacettepe University, Department of Statistics, Ankara, Türkiye
0000-0002-4188-184X sturkan@hacettepe.edu.tr

References

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis, 20*(1), 1–17.

Anselin, L. (2005). Exploring spatial data with GeoDaTM: A workbook. Centre for Spatially Integrated Social Science.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics, 26*(1), 77–104.

Baltagi, B. H. (2005). Econometric analysis of panel data. John Wiley & Sons Ltd.

Bivand, R., Millo, G., & Piras, G. (2021). A review of software for spatial econometrics in R. Mathematics, 9(11), 1276.

Chen, Z., & Haynes, K. E. (2015). Regional impact of public transportation infrastructure: A spatial panel assessment of the US Northeast megaregion. *Economic Development Quarterly, 29*(3), 275–291.

Chen, Z., Barros, C., & Yu, Y. (2017). Spatial distribution characteristic of Chinese airports: A spatial cost function approach. *Journal of Air Transport Management,* 59, 63–70.

Cheung, T. K. Y., Wong, W. H., Zhang, A., & Wu, Y. (2020). Spatial panel model for examining airport relationships within multi-airport regions. *Transportation Research Part A: Policy and Practice*, 133, 148–163.

Daraban, B., & Fournier, G. M. (2008). Incumbent responses to low-cost airline entry and exit: A spatial autoregressive panel data analysis. *Research in Transportation Economics, 24*(1), 15–24.

Efendigil, T., & Eminler, Ö. E. (2017). Havacılık sektöründe talep tahmininin önemi: Yolcu talebi üzerine bir tahmin modeli. *Journal of Yasar University*, 12.

Erdem, U., Mert Cubukcu, K., & Tsiotas, D. (2020). Mapping the topology of the air transport network in Turkey. *Environment and Planning A: Economy and Space, 52*(1), 6–9.

Ergün, M. (2025). The impact of geodemographic factors on airport traffic in Türkiye: An aviation analysis. *Journal of Aviation, 9*(1), 91–99.

Golgher, A. B., & Voss, P. R. (2016). How to interpret the coefficients of spatial models: Spillovers, direct and indirect effects. Spatial Demography, 4, 175–205.

Gülel, F. E. (2013). Mekânsal panel veri modelleri ve Avrupa ülkelerindeki intihar oranları üzerine uygulaması (Doktora tezi). Mimar Sinan Güzel Sanatlar Üniversitesi, Fen Bilimleri Enstitüsü, İstanbul.

Güriş, S. (2015). Stata ile panel veri modelleri. Der Yayınevi.

Karanki, F., Lim, S. H., & Choi, B. J. (2020). The determinants of aeronautical charges of US airports: A spatial analysis. *Journal of Air Transport Management*, 86, 101825.

Lenaerts, B., Allroggen, F., & Malina, R. (2023). Air connectivity and regional employment: A spatial econometrics approach. *Regional Studies, 57*(3), 560–575.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies, 60*(3), 531–542.

Marinos, T., Belegri-Roboli, A., Michaelides, P. G., & Konstantakis, K. N. (2022). The spatial spillover effect of transport infrastructures in the Greek economy (2000–2013): A panel data analysis. *Research in Transportation Economics*, 94, 101179.

Millo, G., & Piras, G. (2012). splm: Spatial panel data models in R. *Journal of Statistical Software*, 47(1), 1–38.

Moran, P. A. (1948). The interpretation of statistical maps. Journal of the Royal Statistical Society: Series B (Methodological), 10(2), 243–251.

Piribauer, P. (2021). SDPDmod: Estimation methods for spatial dynamic panel data models. R package version 0.1. https://CRAN.R-project.org/package=SDPDmod

Şentürk, F. (2019). Mekânsal panel veri analizi: Türkiye'de bölgelerin dış ticaret hacmine göre yakınsaması (Doktora Tezi). Gazi Üniversitesi, Sosyal Bilimler Enstitüsü, Ankara.

Tatoğlu, F. Y. (2018). İleri panel veri analizi. Beta Yayınları.

Tatoğlu, F. Y. (2022). Mekansal Ekonometri Stata Uygulamalı. Beta Yayınları.

Tesfay, Y. Y. (2016). Modified panel data regression model and its applications to the airline industry: Modeling the load factor of Europe North and Europe Mid Atlantic flights. *Journal of Traffic and Transportation Engineering* (English Edition), 3(4), 283–295.

Tirtha, S. D., Bhowmik, T., & Eluru, N. (2023). Understanding the factors affecting airport level demand (arrivals and departures) using a novel modeling approach. *Journal of Air Transport Management*, 106, 102320.

Türkan, S. (2024). Analyzing regional factors influencing passenger, aircraft demand, and freight demand using penalized geographically weighted regression models. *Journal of Geography*, (49), 19–30.

Xiao, F., Wang, J., Xiong, M., & Mo, H. (2024). Does spatiotemporal heterogeneity matter? Air transport and the rise of high-tech industry in China. *Applied Geography*, 162, 103148.

Yang, Y., Hu, M., Yin, J., & Wu, W. (2025). Spatio-temporal evolution and influencing factors of supply–demand coupling and coordination in civil aviation passenger transport. *Applied Sciences, 15*(3).