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RESEARCH ARTICLE

A Comparison of Forecasting Performance of PPML and OLS estimators: The Gravity Model in the Air Cargo Market

Gizem Kaya[1], Umut Aydın[2], Burç Ülengin[3]

[1](Res. Asst.), Istanbul Technical University, Management Faculty, Management Engineering Department, Istanbul, Turkiye
[2](Assist. Prof.), Bandırma Onyedi Eylül University, Ömer Seyfettin Faculty of Applied Sciences, Department of International Trade and Logistics, Balıkesir, Turkiye
[3](Prof. Dr.), Istanbul Technical University, Management Faculty, Management Engineering Department, Istanbul, Turkiye

ABSTRACT
Using international air cargo data from Turkey, this study compares the forecast performance of three different approaches in the air transport literature for the basic gravity model parameter estimation. The first approach uses ordinary least squares to estimate the gravity model, which is frequently utilized in air transport literature. The second approach, like the first, employs the log-linear estimate technique, but unlike the first, it adds a small amount to the observations with a zero-valued dependent variable and includes them in the analysis. The third method is to estimate the gravity model using the Poisson pseudo maximum-likelihood estimator, which is an alternative to the ordinary least square estimator. The forecast performance of the models developed after estimating the equation with three different approaches was compared with error metrics and the Diebold-Mariano test. As a result of the study, the Poisson pseudo-maximum-likelihood estimator was observed to be the estimator with by far the best forecast performance for the total amount of cargo carried. However, the forecast performance of models differs for some cities.

Keywords: *The gravity model; Poisson pseudo-maximum-likelihood, Ordinary least squares, Air cargo, Forecast performance*

Introduction

Airline demand forecasting can be described as forecasting the expected passenger and/or cargo traffic between two destinations in a specific time period, and highly accurate forecasts are crucial to an airline's overall success. When the annual growth rates of the air cargo market are analyzed, one can say that the air cargo market has had a growth trend in the last 10 years, although there have been interesting movements in the growth rates on an annual basis during the Covid-19 period. (Choi, 2023). A high forecasting accuracy rate is a crucial component of an airline's overall success, and cargo volume forecasting has become as vital in forecasting as passenger volume forecasting. Based on these forecasts, airlines can determine whether to open new routes or add flights to existing ones.

Air freight transport volumes have roughly doubled every ten years during the previous few decades, growing at a 50% faster pace than passenger transport traffic during the same era (Feng et al., 2015). This year-on-year expansion rate has recently risen, with a current 11.9% increase above pre-pandemic levels. Air transport is typically the preferred mode of delivery services for time-sensitive and high-value products, and it is projected that goods worth more than US$6.8 trillion (more than 35% of global trade by value) use air cargo companies as a mode of transport, which accounts for a significant portion of earnings for airlines and air carriers. Air cargo contributes 9% of airline revenues on average, which is more than double the income generated by the first-class segment (Desai et al., 2023).

In recent years, the government of Turkey and air cargo participants have increased their investments in the air cargo market in order to grow their worldwide share of the air cargo sector. When all of the phases are finished, Istanbul Airport, which began operations in 2018, will have an annual freight handling capacity of 5.5 million tons, and it is projected that this capacity will lead the airport to become an important hub in global air cargo traffic (IGA, 2021). The data for the country's air freight operations

Corresponding Author: Umut Aydın **E-mail:** uaydin@bandirma.edu.tr
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also illustrate the return on these investments. In the previous ten years, the volume of cargo transported by Turkish airlines has climbed by an annual average of 9.9%. (DHMI, 2021).

The literature review section will show that there are various factors affecting the amount of air cargo carried. The most important of these factors are GDP and population, which indicate the economic size of countries. However, apart from these, studies show that customs tariffs, whether countries are connected by road, the frequency of flights between countries, and many other factors affect the amount of cargo transported. Moreover, it can also be said that the number of passengers carried between airports indirectly affects the amount of cargo transported. This is because air cargo is transported not only by dedicated cargo aircraft but also by passenger aircraft. Although this situation mentioned shows the interaction between air cargo and passenger operations, there are certain differences between airline passenger and cargo transportation. Firstly, in passenger transportation, the capacity is determined as one seat for each passenger carried, while in cargo transportation, such a standard is not possible due to the volumetric and chemical properties of each cargo. While the aircraft used for passenger operations are generally, newly produced aircraft, the aircraft used for cargo operations are usually passenger-to-freighter aircraft that were previously used for passenger operations and then converted into freighters. Moreover, cargo operations are usually carried out during night hours while passenger operations are predominantly carried out during daylight hours (Desai et al., 2023).

There are several approaches for estimating passenger volume. Because no single approach guarantees accuracy, airlines actually compare forecasts from many models. The gravity model is one of the most extensively used forecasting models in this group. The gravity model is an econometric technique that employs traffic between destination pairs as a dependent variable and destination macroeconomic factors as an explanatory variable. Because of the aforementioned characteristics, the gravity model can make traffic forecasts even for destinations that do not have historical traffic data, and this advantage leads to researchers frequently benefiting from the gravity model approach.

As seen by studies that estimate traffic for air transportation, OLS (Matsumoto, 2004; 2007; Grosche et al., 2007; Hazledine, 2009; Zhang and Findlay, 2014; Gong et al., 2014; Gillen and Hazledine, 2015; Cristea et al., 2015; Matsumoto et al., 2016; Hazledine, 2017; Alexander and Merkert, 2017; Matsumoto and Domae, 2018; 2019; Becker et al., 2018 and Alexander and Merkert, 2021) and alternative estimators (Zhang and Zhang, 2016; Grosso and Shepherd, 2011) are frequently utilized in gravity model parameter estimation. The main reason for this is that the log-linear OLS estimator cannot be include in the analysis observations with zero-valued dependent variables. Because of this, some studies increase the amount of traffic in the dependent variable to be sufficient for the analysis to add zero-valued observations. Even if there is no traffic, the potential of the destinations can be included in the analysis.

In the field of air transportation, basic gravity model studies using data on the number of cargo and/or passengers carried between pairs of destinations generally use OLS-based approaches for coefficient estimation. However, subsequent studies have shown that the OLS approach causes problems in basic gravity model coefficient estimation both econometrically and in terms of practical significance, so alternative approaches have been developed. The first alternative approach is to increase the observations with a value of zero as the dependent variable until it reaches 1 in order to be included in the analysis. In this first alternative, the OLS approach is used for the coefficient estimator after the transformation. The second alternative is to use the PPML approach for coefficient estimations using the original dataset without applying any transformation to the dataset. Although the aforementioned approaches are mostly used in the air transport literature for reliable coefficient estimations in basic gravity model estimation, no study has been conducted to evaluate the in-sample and/or out-of-sample prediction/forecast performances of these approaches. With these motivations, in this paper, the prediction and forecast performances of OLS and two alternative approaches to OLS (Represented in this study by OLS* and PPML approaches) are compared. Moreover, it has been tried to determine which approach gives more reliable coefficient estimations for basic gravity model coefficient estimation in the data set with which features. Thus, the estimator with the best prediction/forecast performance in Turkey's international air cargo data will be determined and provided for airline businesses' decision-making processes such as capacity and demand planning.

The remainder of this paper is organized as follows. The second section is a review of the literature on the prediction and forecast of air transportation traffic volume publications, with a focus on research that employed gravity models. Section 3 includes a brief introduction of the PPML and OLS estimators, as well as the basic gravity model, describes the data set and models, and provides some preliminary information on error metrics and the Diebold-Mariano test. The parts that follow include empirical findings about the comparisons of gravity model approaches in terms of forecast and prediction, and also conclusions and future research opportunities respectively.

Literature review

Around the end of the 1950s, studies aimed at projecting demand for the air transport business started to emerge in the literature. These studies were primarily concerned with evaluating the demand that may come from airline market tactics, as well as the elements that drive that demand. The literature on the subject of air transportation has been one in which studies have differed in terms of methodology from the decade when it began to emerge, so much so that Lansing et al. (1961) used cross-sectional data in their research, while Barlett (1965) and Long (1966) employed time series data. In addition to these investigations, Joun and Mize approximated volume in 1966 and 1968 utilizing either cross-sectional or time series data. (Schultz, 1972).

In the decades that followed, researches such as Kanafani (1983) and Ben-Akiva and Lerman (1983) attempted to make inferences about potential customers by evaluating passenger preferences using the multinomial logit approach. Moreover, the researches of Maddala (1983) and Schneider (1986) assumed that the variables employed may have distributions that differed from the normal distribution. These studies, as well as others, put forward a variety of research examining demand in the field of air transportation.

Researchers gained access to and can analyze more data as a consequence of technology advancements in the 1990s. Short-term forecasting (Blume et al., 1995), long-term forecasting (Wickham, 1995), and hybrid approaches (Danilov, 1997) were all used to categorize time series research. Around that time, academics began to combine econometric techniques with machine learning technologies. Artificial neural networks (ANN) were used in Nam and Schaefer's (1995) and Law and Au's (1997) research to estimate worldwide airline demand and Hong Kong airline passenger demand, respectively.

In the 2000s, studies employing econometric variables as predictors of airline passenger and/or cargo demand forecasts began to emerge in the literature. Alekseev and Seixas (2009) employed GDP as a predictor and conducted airline passenger demand with ANN, reporting that ANN outperformed standard econometric approaches in the results they received. Fernandes and Pacheco (2010) employed a linear Granger causality test to analyze the relationship between GDP and domestic air passenger traffic in Brazil and concluded that there is a one-way causal relationship between economic growth and domestic air transport demand. Using a linear Granger causality analysis, Hakim and Merkert (2016) investigated the causal link between air transport and economic growth in the southeast Asian area and concluded that there is a uni-directional causation running from GDP to air transport demand. Baker et al. (2015) discovered a strong bidirectional interaction between economic growth and air transport demand in regional, rural, and remote towns in Australia. According to the findings of Baker et al. (2015), maintaining airport facilities is critical since it affects the regional economy. Suryani et al. (2010), on the other hand, discovered that airfare impact, level of service impact, GDP, population, number of flights per day, and dwell time all had an influence on air passenger numbers.

Panel data estimators, on the other hand, have been used by scholars attempting to estimate both passenger and cargo demand in aviation since the early 2000s. Panel data estimators have an advantage over other estimators in that they can obtain information from the units in both the cross-sectional and time series dimensions (Tatoglu Yerdelen, 2018). Among these estimators, the gravity model, a specialized panel data estimate approach, emerges as a method widely utilized by researchers attempting to forecast air transportation demand. The gravity model has been used successfully to analyze bilateral flows in international trade, transportation, marketing, migration, and a variety of other spatially connected fields (Bergeijk and Brakman, 2010). The model in transportation research describes the mobility of goods and people between pairs of destinations in terms of income and distance, as well as other variables that may support or impede the flow of goods and people. The gravity model has achieved popularity among international trade economists and policymakers for three reasons, according to Baier and Bergstrand (2010): powerful theoretical economic basis, sufficiently good explanatory power, and policy relevance for analyzing various free trade agreements. Furthermore, using this method, researchers were capable of predicting demand in regions with no airports or with less traffic during the existence of an airport.

Table 1 summarizes studies in the field of air transportation that attempt to model passenger and/or cargo flow using the gravity model.

Matsumoto's (2004) study is the first to employ the gravity model method to model cargo and passenger traffic in the field of air transportation, as shown in Table 1. The basic gravity model variables, population, distance, and GDP, as well as dummy variables created for cities, were employed in this study, and passenger and cargo traffic was attempted to be explained using these variables. In this study, the OLS estimator was used to estimate the augmented gravity model coefficients, and as shown in Table 1, there have been studies conducted using various gravity model approaches in the field of air transportation.

Although gravity model studies work with panel data, these studies (Matsumoto, 2004; 2007; Grosche et al., 2007; Hazledine, 2009; Grosso and Shepherd, 2011; Zhang and Findlay, 2014; Gong et al., 2014; Gillen and Hazledine, 2015; Cristea et al., 2015; Matsumoto et al., 2016; Hazledine, 2017; Alexander and Merkert, 2017; Matsumoto and Domae, 2018; 2019; Becker et al., 2018 and Alexander and Merkert, 2021) made cross-sectional coefficient estimates and reported the changes of these coefficients over the years. On the other hand, studies such as Yamaguchi (2008), Hwang and Shiao (2011), and Zhang and Zhang (2016) made gravity model parameter estimations by using panel data models.

Table 1 also shows that the OLS estimator is predominantly used in gravity model studies for air transport, but Santos and Tenreyro (2006) show that the error term of the log-linear OLS estimator is heteroscedastic. Moreover, Westerlund and Wilhelmson (2011) state that the reason why the coefficients of the gravity model are estimated to be biased by OLS is due to the presence of zero-valued observations in the data set. As a result of this situation, researchers tried to estimate the gravity model coefficients with alternative estimators in forecasting airline passenger and cargo traffic.

Table 1. The Gravity Method-Specific Air Transportation Studies

Author	Traffic	Estimator(s)
Aydın and Ülengin (2022)	Cargo	PPML, OLS
Alexander and Merkert (2021)	Cargo	OLS
Matsumoto and Domae (2019)	Cargo and Passenger	OLS
Becker et al. (2018)	Passenger	OLS
Matsumoto and Domae (2018)	Cargo and Passenger	OLS
Alexander and Merkert (2017)	Cargo	OLS
Hazledine (2017)	Passenger	OLS, Probit
Matsumoto et al. (2016)	Passenger	OLS
Zhang and Zhang (2016)	Passenger	Fixed Effect, Random Effect
Cristea et al. (2015)	Passenger	Poisson, OLS
Gillen and Hazledine (2015)	Seats, Flights, Airfares	OLS
Gong et al. (2014)	Cargo	OLS
Zhang and Findlay (2014)	Passenger	OLS
Grosso and Shepherd (2011)	Cargo	PPML
Hwang and Shiao (2011)	Cargo	Pooled OLS, Fixed Effect, Random Effect
Hazledine (2009)	Passenger	OLS
Yamaguchi (2008)	Cargo	Random Effect, Maximum Likelihood, Two Step Least Squares, Pooled OLS, OLS
Grosche et al. (2007)	Passenger	OLS
Matsumoto (2007)	Cargo and Passenger	OLS
Matsumoto (2004)	Cargo and Passenger	OLS

The first alternative is to determine a threshold value for the observations to be included in the data set and continue the analysis with the observations whose dependent variable is above this threshold value. An example of this approach is Matsumoto, 2004; 2007; Grosche et al., 2007; Hazledine, 2009; Grosso and Shepherd, 2011; Zhang and Findlay, 2014; Gong et al., 2014; Gillen and Hazledine, 2015; Cristea et al., 2015; Matsumoto et al., 2016; Hazledine, 2017; Alexander and Merkert, 2017; Matsumoto and Domae, 2018; 2019; Becker et al., 2018 and Alexander and Merkert, 2021 studies can be given. Dropping zero-valued data in the least squares technique, however, leads to considerable bias in sample selection, as reported by Gül and Tatolu (2018).

According to Zhang and Zhang (2016), a second alternative is to add a little value to the zero-valued observations in the data set before the analysis to use these observations in the log-linear estimation. This strategy, however, can be employed if the zero-valued observations are randomly distributed, according to Zhang and Zhang (2016), and even in such circumstances, Helpman et al. (2008) should be used for sample selection. Thus, observations having a value of zero in the dependent variable can be included in the analysis.

The PPML estimator, which was employed in the study by Westerlund and Wilhelmson (2011) as an alternative to OLS, is another approach to deal with the problem of the zero-valued dependent variable. This estimator just logarithmically transforms the explanatory variables employed, allowing data with a zero dependent variable to be included in the analysis. Furthermore, because it is a non-linear estimator, it produces more reliable estimations than OLS. Further to that, Aydın and Ülengin (2022) show in their study using Turkey's domestic air cargo data for the period of 2012 and 2020 that the coefficient estimates obtained with the PPML estimator of the gravity model are more consistent and reliable than the OLS parameter estimates.

Aside from the Grosso and Shepherd (2011) research, Table 1 reveals that gravity model studies in the field of air transportation employ the OLS estimator. However, to the best of our knowledge, no study comparing the prediction/forecast capabilities of the three approaches utilized in gravity model parameter estimates has been found in the literature. Choosing the best estimator for prediction/forecast performance is crucial for airlines since forecasting future demand has an impact on all of the company's policies and strategies. Thus, this study compares the prediction and forecasting performance of three alternative methodologies employed in gravity model estimation using Turkey's international cargo data, with the goal of determining which one performs the best. When comparing these three alternative approaches based on PPML and OLS estimators, error metrics will be used as in the studies such as Robert et al. (2009), Tratar and Strmčnik (2016), Su et al. (2019) and Zhang et al. (2019). At this stage, the three approaches are compared using basic error metrics such as RMSE and MAE, which are commonly used in forecast studies; the MAPE metric, which is unaffected by the unit of measurement of the data and produces more stable results than the basic metrics; and Theil-U statistics, which compare the obtained models with the naive model. Since the prediction/forecast values and actual values obtained with the Gravity model are aggregated and analyzed annually, it is not cumbersome to use these metrics when comparing prediction/forecast performances. In other words, if there are zero-valued observations in the actual values of the models whose prediction and forecast performance are compared, then appropriate error metrics should be used for intermittent data. For this reason, although the actual values of the models whose prediction and forecast performance are compared in this study do not contain zero, the SMAPE metric is also calculated and reported. In addition, the Diebold-Mariano (DM) test, which tests the statistically significant difference between the two prediction models, was also performed.

Methodology

Three different models were introduced in this section for the air cargo volume prediction issue. The first of these is to remove the observations with zero dependent variables from the data set and to estimate the gravity model coefficient with the OLS estimator. In the second approach, the OLS estimator is also used, but unlike the first approach, the zero-valued observations are made suitable for the logarithmic transformation by adding 1 tonne to each observation's cargo value. In the third approach, parameter estimations were made with the PPML estimator, which is used as an alternative to OLS, and no changes were applied to the data set in this last approach. In this section, a brief introduction is provided about the gravity model and the OLS and PPML estimators used for gravity model coefficient estimations.

The Gravity Model

The gravity model is based on Isaac Newton's gravitational law and is formulated as follows:

$$F_{ij} = G\frac{m_i m_j}{d_{ij}^2} \tag{1}$$

F refers to the gravity attraction power between items i and j in equation (1); m represents the masses of the i and j objects in the equation; d_{ij} refers to the distance among them; and G is the constant of gravitation. Isard and Peck (1954) adapted the fundamental concept of gravity, which is called Newton's law in physics, for commerce worldwide in the periods that followed. Tinbergen, on the other hand, laid the mathematical groundwork for the approach in 1962, and the gravity model modified for international commerce is as follows.:

$$X_{ij} = \beta_0\frac{(Y_i)^{\beta_1}(Y_j)^{\beta_2}}{(D_i j)_3^{\beta}} \tag{2}$$

The suffixes i and j in equation (2) represent the countries that are sending and receiving the goods. X_{ij} represents commerce between economies i and j, whereas Y represents the economic magnitude of these nations. In the formula's denominator, D_{ij} refers to the distance in kilometers between nations. Tinbergen (1962) used Isaac Newton's law of gravity to economics for global commerce, and this approach allows for prediction by describing the model in its entire logarithmic form. As a consequence, logarithmic equation (3) is as follows:

$$lnX_{ij} = \beta_0 + \beta_1 lnY_i + \beta_2 lnY_j + \beta_3 lnD_{ij} + u_{ij} \tag{3}$$

Here β_1 and β_2 should be positive while β_3 should be negative according to the theory. If the data set covers all units in the population, the fixed effects estimation technique should be used when working with panel data. Both the fixed effect estimates with the dummy and the within transformation drop the time-invariant distance variable in this situation (Gül and Tatoğlu, 2018). Furthermore, because the logarithm of zero is undefined, the dependent variable is omitted from the model. Dropping zero-valued observations causes considerable bias in sample selection in the least squares approach (Gül and Tatoğlu, 2018). In heterogeneous datasets with zero-valued observations, Gómez-Herrera (2013) proved that utilizing different estimators resulted in biased coefficients. Using Monte Carlo Simulation, Santos and Tenreyro (2006) demonstrated that when the classical gravity model is linearized, the assumption of a constant variance for the error is collapsed. According to Aksöz Ylmaz (2021), the PPML estimation approach produced effective estimators in the presence of heteroskedasticity. Furthermore, Westerlund and Wilhelmson (2011) demonstrate that having a value of zero in the dependent variable produces bias in the coefficient estimate of the constructed linear logarithmic model. The PPML estimator doesn't use the logarithm of the dependent variable in this situation, and the equation is as follows:

$$X_{ij} = exp(\beta_0 + \beta_1 lnY_i + \beta_2 lnY_j + \beta_3 lnD_{ij})u_{ij} \tag{4}$$

Westerlund and Wilhelmson (2011) found that the bias of the PPML is lower than that of the OLS-based techniques and that it performs better in their analysis. This finding inspires this study to compare these two techniques (three alternative ways) using Turkey's international air cargo data in the form of destination-paired flights.

In summary, the PPML estimator helps researchers to be in the safe zone in situations that may be encountered when using the OLS estimator in coefficient estimation in terms of the following features:

1. The fact that all variables are log-linear in gravity model coefficient estimation with OLS causes the variance of error terms to be heteroskedastic. The PPML estimator provides efficient coefficient estimates even in the presence of heteroskedasticity.
2. Since the ln of the dependent variable is taken when estimating with OLS, which is a log-linear estimator, observations with a value less than 1 cannot be included in the analysis and this causes sampling bias. In the PPML estimator, the dependent variable is used without any transformation.
3. If there are zero-valued observations in the dependent variable in the data set used, these observations cannot be included in the analysis with the least squares estimator, but these observations can also be used with the PPML estimator using maximum likelihood. Thus, in the specific case of this study, estimates can be made about the potential traffic volumes for cities without airports or airports with airports but without cargo and/or passenger traffic.

Data Set and Equations

In terms of regions, Asia-Pacific stands out with the highest passenger traffic worldwide. According to their population density, Asia contains about 59.5% of the world's population, and it accounts for about 34% of the global airline passenger traffic. However, Europe includes only 9.6% of the world's population, it comprises 23% of the global airline passenger traffic. On the other hand, Turkey has great importance for the commercial air transportation sector due to its geographical location, both being located in Europe and being a transfer center on global flight routes. The amount of cargo transported has increased by approximately 200% despite the pandemic up to 5 years ago (World Bank, 2023).

The dataset for the study contains bilateral cargo movement between the 49 airports in various cities in Turkey and airports in 127 different countries as an independent variable. However, GDP and population statistics for cities with airports in all nations were not available on a city-by-city basis. As a result, the data set uses bilateral cargo traffic between Turkish airports and airports in 127 other countries. While creating the dependent variable, the airports in the destination pairs were aggregated according to the countries they are located in. (e.g., when creating the Germany-Istanbul Airport observation, the total amount of transported cargo sent from Istanbul Airport to all airports in Germany in 2019 was used, vice versa). During the creation of the dataset, the airports in Turkey and international airports where cargo is transported between airports in Turkey are aggregated based on the countries where they are placed, which are used as a destination pair. This is because, as mentioned before, GDP-per-capita and population variables are available for the cities in Turkey, while these data are not available for all of the cities where the airports abroad are located. For this reason, GDP-per-capita and population variables for airports in Turkey are the values of the cities where they are located. The descriptive statistics of the variables can be seen in Table A1 (in the appendix).

To compare the prediction performances of three alternative approaches that employ OLS and PPML estimators for the basic gravity model parameter estimation, this study provides three different model predictions, two models using the OLS estimator and a model using the PPML estimator. The model estimations are based on pooled data, and the equations are mathematically represented as follows:

$$lnCargo_{ijt} = \beta_0 + \beta_1 ln(Population_{it} * Population_{jt}) + \beta_2 ln(GDP_{it} * GDP_{jt}) + \beta_3 lnDistance_{ijt} + u_{ijt} \tag{5}$$

$$Cargo_{ijt} = exp(\beta_0 + \beta_1 ln(Population_{it} * Population_{jt}) + \beta_2 ln(GDP_{it} * GDP_{jt}) + \beta_3 lnDistance_{ijt}) u_{ijt} \tag{6}$$

The total cargo moved between airport i and nation j is the dependent variable in the preceding equations. For airport i, the population variable is the total population of the province where that airport exists, and for nation j, it is the entire population of the country where the airports are situated. The GDP per capita variables follow the same logical thinking and illustrate the economic progress of Turkey's cities and countries. The distance variable is the distance traveled in kilometers between airport i and nation j; nevertheless, these variables are considered as a mean of the distances between airports within nations and airports in Turkey. For example, while computing the travel distance between Sabiha Gökçen Airport and Germany, the mean distance between all airports in Germany is considered. Moreover, t subscribing also represents the time (year). If the year effect is significant in the established models, dummy variables to represent the years can be also added to these equations (5) and (6).

As one can see, equation (5) employs the natural logarithm of the dependent variable, but equation (6) employs no transformation of the dependent variable. This is the most significant distinction between OLS and PPML estimations. Despite the fact that the dependent variables are used differently, both equations utilize the natural logarithm of the explanatory variables.

The data set employed in the analysis ranges from 2012 to 2019. The data for 2020 is utilized as an out-of-sample to test the model's forecast performance. The cargo variable, which measures the yearly cargo moved between airports in Turkey and nations and is the dependent variable in the equations, was gathered from the annual Statistical Yearbook publications of the General Directorate of State Airports Authority (DHMI, 2020). Population and GDP statistics were gathered from the Turkish Statistical Institute (TURKSTAT, 2021) database and the World Bank database (World Bank, 2021). The Airport Package in R programming language was employed to generate the distance variable among airports (https://cran.r-project.org/web/packages/airportr/airportr.pdf), and the cells that remain were then filled via the Air miles calculator (www.airmilescalculator.com) and the airport distance calculator (www.airportdistancecalculator.com).

Metrics of Forecasting Performance

To evaluate the forecasting performance of each model, five statistical measures are used: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), and Theil U1 (TU1). Each metric's definition is provided below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

$$MAPE = \sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{Y_i}\right| \times \frac{100}{n} \tag{9}$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{(y_i + \hat{y}_i)/2} \tag{10}$$

$$TU1 = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\hat{y}_i^2}\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2}} \tag{11}$$

All the metrics given above are used to reflect the five aspects of the prediction and forecast errors and they all work with the same logic: the smaller it is, the better the prediction/forecast performance of the established model. In addition to the calculated error metrics, the DM test statistic was also calculated in order to compare the prediction models obtained.

DM is used to determine whether two predictions are statistically different from each other (Diebold and Mariano, 1995). The calculation of the DM statistic is as shown below:

$$DM = \frac{\overline{d}}{\sqrt{[Y_0 + 2\Sigma_{k=1}^{h-1}Y_k]/n}} \tag{12}$$

Here $\overline{d}$ is the average of the difference of the error terms of the two predictions. Y_k represents the autocovariance in the kth lag. The null hypothesis of the DM test is E(d_t) = 0 and DM follows a standard normal distribution. Thus, there is a significant difference between the forecasts if |DM| > z_{crit} where DM~ N(0,1).

Forecasting Performance of Estimators

According to Grosche et al. (2007), the most significant element in forecasting airline traffic is model estimation, and models with good estimation performance would also have good forecasting performance. But this case is valid because there is no overfitting in the prediction. However, equation estimations were conducted utilizing three different approaches in order to compare the estimation capabilities of the OLS and PPML estimators considering their Pseudo R-sq / R-sq to check overfitting. The in-sample coefficient estimations are shown in Table 2:

Table 2. Pooled PPML, OLS, and OLS* results

	PPML	OLS	OLS*
Population	1.26***	1.03***	0.19***
	(0.02)	(0.04)	(0.00)
GDP	1.02***	0.52***	0.13***
	(0.04)	(0.05)	(0.00)
Distance	-1.42***	-0.19*	-0.17***
	(0.06)	(0.10)	(0.00)
2013	0.00	0.24	0.00
	(0.20)	(0.28)	(0.02)
2014	0.17	0.56**	0.00
	(0.20)	(0.31)	(0.03)
2015	0.39*	0.22	1.04*
	(0.20)	(0.27)	(0.02)
2016	0.57***	0.44	0.03
	(0.20)	(0.28)	(0.02)
2017	0.68***	0.26	0.04*
	(0.20)	(0.28)	(0.02)
2018	0.77***	0.52*	0.04*
	(0.20)	(0.28)	(0.02)
2019	0.95***	0.64*	0.05**
	(0.20)	(0.28)	(0.02)
Constant	-44.01***	-36.79***	-6.79***
	(1.15)	(1.81)	(0.25)
N	35150	1512	35150
Pseudo R-sq / R-sq	0.69	0.27	0.10
Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01			

Table 2 presents the estimations of the coefficients for the basic gravity model using three alternative techniques and two different estimators. According to Hwang and Shiao (2011), while estimating the gravity model using panel data, population or distance variables capture unit fixed effects; hence, dummy variables are included in the pooled PPML and OLS models to observe the time effect. Dummy variables that are statistically significant indicate that the volume of cargo handled in the relevant year is higher than in 2012. All of the basic gravity model variables are expected to be statistically significant, and all of the basic gravity model variables are statistically significant at the 0.05 significance level, with the exception of the distance variable of the OLS model. The coefficients of GDP and population variables were found to be positive, providing support to the idea that massive things attract each other. Because the distance variable is a proxy for cost, it is expected that the coefficient will be negative. The PPML and OLS* approaches, which did not omit the observations with 1 tonne or less dependent variables from the data set, worked with 35150 observations in the equation estimations, but the OLS approach only worked with 1512 observations because these observations were dropped by the OLS approach.

As shown by Aydın and Ülengin (2022), the OLS estimator of gravity model coefficients underestimates the effects of explanatory variables when compared to the PPML estimator. Table 2 demonstrates the coefficient estimates generated with the PPML estimator. When comparing predicting and forecast performances, it will be observed in the next sections of the study that OLS-based forecasting approaches had better forecast performance for airports with lesser traffic. This is due to the fact that OLS-based approaches underestimate the explanatory variable effects, such that while it has poor forecast performance for airports with higher traffic, it underestimates the effect for airports with lower traffic, resulting in lower forecast values than the PPML estimator. Figure 1 shows the total amount of international cargo carried annually in the squares in Turkey in 2012 and 2019, and the predictions/forecasts for the same period made with three different approaches.

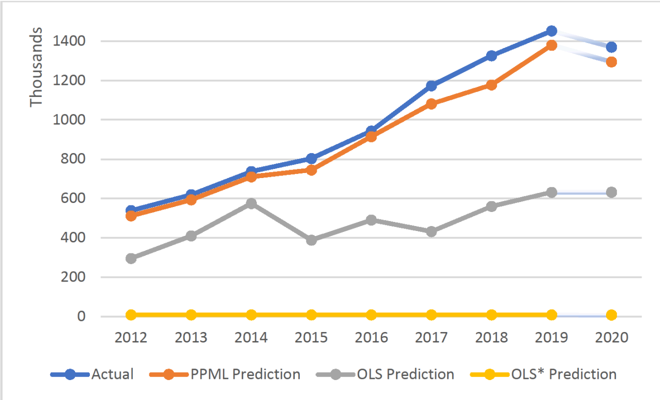

Figure 1. Total annual international air cargo handled in Turkey between 2012 and 2019, as well as predictions/forecasts for the same years

The blue in Figure 1 represents the total amount of international cargo carried in the aerodromes in Turkey in the period of 2012 and 2020, the orange one is the PPML predictions, the grey line is the OLS predictions and the yellow one is the second OLS (OLS*) predictions between 2012 and 2019. For the year 2020 forecast performances are given. Figure 1 shows that the fitted values and forecasted values obtained with the PPML estimator of the same variable as the blue line representing the annual amount of international cargo carried in Turkey are very close over the years. In other words, the PPML estimator predicts the total amount of international cargo carried by the airports in Turkey better than the other two approaches using the OLS estimator. Among the three alternative approaches, the second OLS (OLS*) approach is the worst predictor of the annual amount of international cargo handled at Turkey's airports. The OLS* approach makes a gravity model parameter estimation with the OLS estimator, which is a log-linear estimator, by increasing the dependent variable values of the observations with a value from 0 to 1 (adding 1 to each observation and then taking the natural logarithm). The OLS* approach tries to pass the best line that aims to make predictions among the data points in the data set after making the dependent variable values of the observations with a value of 0 as 1. Figure 1 shows that the OLS* approach systematically underestimates the total cargo traffic and the dependent variable transformation performed in the dataset can be seen as the reason for this. Because the high amount of 1 value in the data set pulls down the best line that is tried to be obtained for prediction.

In order to compare the prediction and forecast performances of the obtained equations, the prediction error benchmarking metrics also are calculated and the Table is shown in Table 3:

Table 3. Prediction performance of the alternative gravity model approaches

Prediction	**RMSE**	**MAE**	**MAPE**	**SMAPE**	**Theil U1**
PPML	**72355**	**59849**	**5**	**6**	**0.03**
OLS	537850	476346	47	63	0.36
OLS*	991766	940828	99	196	0.98
Forecast	**RMSE**	**MAE**	**MAPE**	**SMAPE**	**Theil U1**
PPML	**112761**	**33296**	**97**	185	**0.33**
OLS	188363	41455	109	185	0.72
OLS*	221934	37982	13477	**129**	0.99

It is important to highlight that the PPML estimator provides the best estimate in all metrics among the three alternative approaches that estimate the total volume of cargo handled annually in Turkey between 2012 and 2019. The squares of the difference between fitted and actual values, or absolute values, are used to evaluate prediction and forecast performance using RMSE and MAE as alternatives. SMAPE is a metric for intermittent data with zero actual value observations, whereas MAPE is a scale-free metric used as an alternative to basic metrics. Table 3 indicates that predictions and forecasts generated using the PPML estimator had much superior performance than the other two OLS-based techniques in calculated measures. Furthermore, the TU1 is a statistic that takes a value between 0-1 that represents prediction accuracy, and the closer this value is to 0, the more accurate prediction it is. Table 3 shows that the PPML estimator outperforms the other two alternatives in predicting Turkey's annual international air cargo traffic, with a TU1 statistical value of 0.03. OLS approach, one of the log-linear estimators, has above-average performance in the prediction of annual total international cargo traffic with 0.36 TU1 statistics, whereas OLS* estimator with 0.98 TU1 statistical value has been observed as an approach with poor performance in the prediction of annual total international air cargo traffic for 2012 and 2019.

From the equation estimates obtained by the three different approaches, Table 3 demonstrates that the PPML estimator has the best predicting and forecasting ability. The PPML estimator is an estimator that can incorporate observations with zero-valued dependent variables in the analysis; thus, it has the greatest performance in three of the five error metrics and the second-best performance in two metrics. In four of the five measures, the OLS* procedure, which includes zero-valued observations in the analysis by slightly increasing them, produced the worst-performing equation estimations.

In addition to the error metrics comparison, the DM test was performed, which evaluated the prediction performance of the techniques over the error metrics, and the test statistics are provided in the table below.

Table 4. DM test statistics for three approaches

	PPML vs. OLS	PPML vs. OLS*	OLS vs. OLS*
İstanbul	-1.77*	-2.34**	-2.87***
Ankara	2.70***	2.72***	2.02**
İzmir	2.69***	3.03***	1.97*
Antalya	1.69*	2.56**	1.94**
Kayseri	-0.36	2.57**	2.04**
Adana	-0.35	2.62***	2.04**
Total	1.69*	2.22*	2.69***
* p<0.10, ** p<0.05, *** p<0.01			

Table 4 shows the DM statistics which compares the prediction performances of the estimators and when one evaluates the prediction performances of three different approaches for the international air cargo volume of Turkey, Table 4 shows that the PPML estimator has the best prediction performance, as the absolute DM statistic is 1.69 when the PPML and OLS approaches are compared, indicating that the PPML estimator has better prediction performance at the 0.10 significance level. When the PPML and OLS* approaches are compared, the absolute DM statistic is 2.22, and the PPML estimator outperforms the OLS* estimator at the 0.05 significance level. When the methodologies utilizing the OLS estimator are compared, the OLS approach outperforms the OLS* approach (Absolute DM statistic = 2.69). When the situation in the Aerodrome breakdown is analyzed, the DM test statistics show that the prediction performance of the PPML estimator is better than the OLS-based estimators in Turkish airports with more international air cargo traffic than other airports. However, when cargo traffic at the airport is relatively lower, the OLS approach, which determines the threshold value for the dependent variable, tends to outperform other approaches in terms of prediction performance. For example, according to the DM statistics shown in Table 4, while there is no statistically significant difference in prediction performance between the OLS estimator and the PPML estimator in the estimation of the cargo traffic of Adana airport, it is seen that the OLS estimator has a statistically significantly better prediction performance than the OLS* estimator.

The findings show that the PPML estimator, which is a non-linear estimator of the gravity model estimation of Turkey's total international amount of air cargo carried, has a far better performance than the log-linear estimator OLS approaches. In order to examine the situation in the unit breakdown, in other words, in the airport breakdown, error performance metrics evaluations were performed by making use of annual aggregated predictions for the airports with the highest international cargo traffic with a dependent variable greater than zero. Figure 2 shows the actual values and fitted values of the 8 airports where the most international cargo is transported. In addition, forecast performances for 2020 on a city basis are also included.

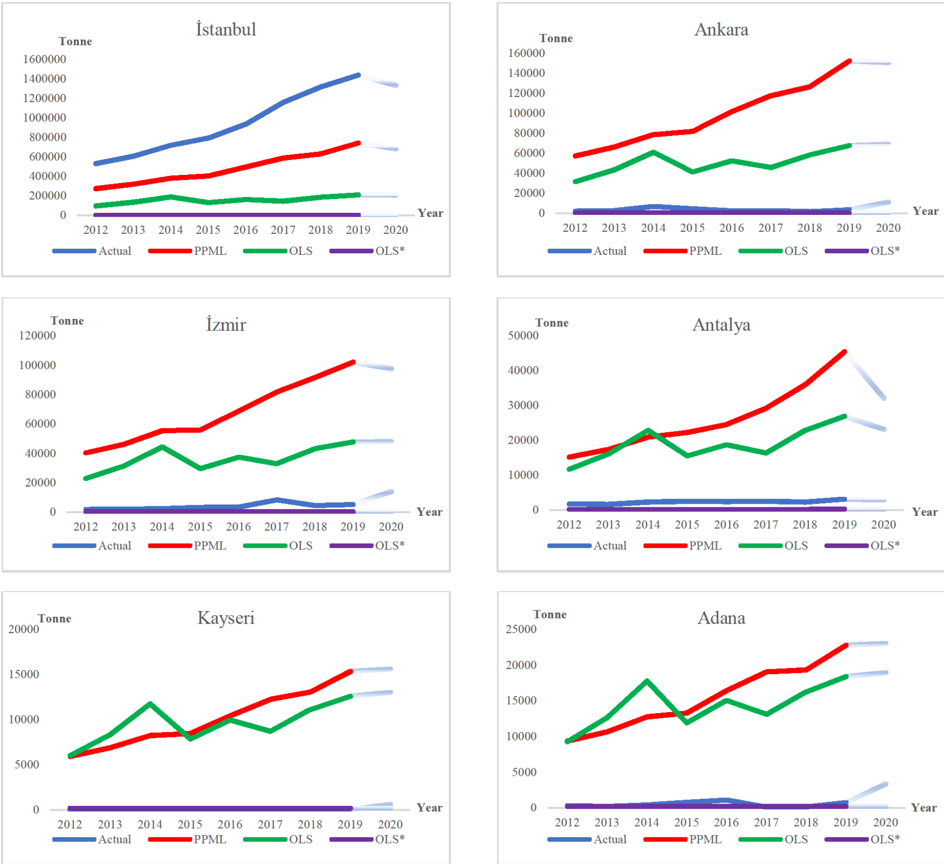

Figure 2. Actual and fitted/forecasted values of airports with the most international cargo carried in 2012 and 2020

Three main airports in Istanbul handle about 90% of international air cargo carried in Turkey so, one can say that the airports in Figure 2 represent almost all airports that operate in Turkey. When the total volume of international air cargo and its predictions and forecasts for the province of Istanbul are analyzed in Figure 2, it is clear that the PPML estimator has the best performance among the three estimation approaches. When the remaining 7 aerodromes are evaluated, it is apparent that the fitted values of the OLS* estimator follow the almost same path as the real values. The fitted values of the OLS* approach get closer to the actual values when the volume of cargo handled at airports is relatively lesser. In addition, a comparable figure for Istanbul was created and added to the appendix. Figure A1 illustrates predictions and actual value comparisons for the six countries with the most cargo transported with Istanbul in 2019. When the figure is examined, it is clear that the PPML estimator outperforms the other estimators in terms of prediction performance.

Table 5 summarizes the error metrics that evaluate the prediction performance of three alternative approaches utilized in the gravity model estimate in the airport breakdown in Figure 2.

Table 5 shows that the PPML estimator is the approach with the best prediction performance in all metrics in the annual cargo traffic prediction of the airports located in Istanbul. However, as the international cargo traffic carried at the airport is less, it is seen that OLS-based approaches have better prediction performance. In the RMSE, MAE, and MAPE metrics, the OLS* approach, which is used by adding to make the dependent variable values greater than 1 during the gravity model estimation, is seen to have better performance than the OLS approach, which determines the threshold value for the dependent variable and applies sample selection. However, in the Theil-U statistics, which compares the prediction accuracy of the alternative approaches, the finding that the OLS approach has better performance is highlighted in Table 5. Moreover, as the amount of cargo carried in the airports is relatively small, it is seen that all three different approaches used in the estimation of the gravity model have almost the same prediction performance as the naive model. In fact, while the ratio of observations with a value less than 1 to all observations in the data set for Istanbul Airport is 16%, it is 79% for Ankara, 86% for Izmir, 81% for Antalya, 93% for Adana and 99% for Kayseri. This shows that the OLS* estimator has better performance as the proportion of observations with a dependent variable value less than 1 in the data set increases.

In summary, Table 5 shows that there are serious variations in the prediction performances of these three alternative approaches used in the estimation of the gravity model in the airport breakdown. While the PPML estimator has an error margin of 48.66%

Table 5. Prediction performances of alternative estimation approaches in airports breakdown

Airport(s)	Estimator	RMSE	MAE	MAPE	SMAPE	Theil U1
İstanbul	PPML	**486168**	**458160**	**48**	**64**	**0.32**
	OLS	833025	780931	82	140	0.72
	OLS*	987198	935750	99	199	0.99
Ankara	PPML	99377	94473	3755	186	0.94
	OLS	48155	46947	1811	176	0.87
	OLS*	**3249**	**2850**	**90**	**165**	**0.87**
İzmir	PPML	66679	63815	1854	179	0.88
	OLS	33164	32269	1024	**162**	**0.80**
	OLS*	**4121**	**3599**	**92**	172	0.90
Antalya	PPML	25725	24053	1035	166	0.84
	OLS	17147	16584	733	**155**	**0.78**
	OLS*	**2114**	**2068**	**90**	165	0.83
Adana	PPML	15600	14977	6612	188	0.93
	OLS	14114	13820	5696	187	0.93
	OLS*	**420**	**304**	**59**	**74**	**0.55**
Kayseri	PPML	10508	10053	237568	199	0.99
	OLS	9744	9523	255149	199	0.99
	OLS*	**174**	**174**	**5375**	**185**	**0.91**

on average in Istanbul, where the amount of cargo carried is relatively high, it makes an average of 200% error in estimation in airports where the annual amount of cargo carried is limited, for example, Kayseri Airport. However, the OLS* approach shows almost opposite performance to the PPML estimator. For example, while the OLS* approach has an average of 200% prediction error in Istanbul, this error averages down to 75% in airports with relatively low cargo traffic. On the other hand, the difference between fitted values and actual values obtained from the estimation of the OLS estimator of the gravity model is around 150% for all aerodromes analyzed on average.

Conclusion and Further Research Opportunities

The studies in the literature broadly utilize three different approaches to estimate the gravity model parameters in the field of air transportation. In the first approach, a threshold value is determined for the observations to be included in the data set and the analysis continues with the observations whose dependent variable is above this threshold value. Literature review showed that some studies estimated the airline passenger and/or cargo traffic using the gravity model, taking advantage of this approach. However, due to the threshold used in these studies, observations with a zero dependent variable cannot be included in the analysis. If the zero-valued observations are distributed randomly, sample selection for the units to be included in the analysis can be made, and the dependent variable values of the observations can be included in the analysis by slightly increasing them (Zhang and Zhang, 2016). However, in both of these approaches, the OLS estimator is utilized, and Santos and Tenreyro (2006) show that the homoscedasticity assumption is violated in the estimate of the gravity model with OLS, and it has biased coefficient estimations. In this situation, the PPML estimator is utilized as an alternative estimator for the gravity model parameter estimation.

All of these studies have one thing in common: they all propose models that attempt to predict possible demand for air transportation. To the best of our knowledge, no study has been conducted that compares the performance of these approaches utilizing air transport data. As a result, the purpose of this study is to assess the estimation performances of three different approaches employing the PPML and OLS estimators. According to Grosche et al. (2007), a good estimation performance is required for an equation to produce effective forecasts.

The primary goal of this study is to compare the prediction and forecasting performance of three different approaches using five error metrics, considering the actual and fitted/forecasted values of the dependent variable. In terms of the total amount of cargo carried, the PPML estimator was by far the best of the three different approaches, whereas the OLS* approach was observed to be the worst-performing technique. Furthermore, the three approaches were compared in pairs using the Diebold-Mariano test, and again, while the PPML approach performed best, the OLS* approach ranked worst.

As a result of this research, the PPML estimator outperforms the OLS estimator for organizations who seek to forecast air transport traffic. However, there are certain research limitations that need to be handled. To begin, the data set utilized in this study is Turkey's international air cargo data, and the dependent variable is the total traffic between two locations in the t period due to data availability. Although the studies in the literature (Hwang and Shiao 201; Gon et al., 2014) employ the dependent variable in this form, future research utilizing the origin-destination data set can make comparisons of the alternative estimation techniques for the gravity model. Furthermore, studies that use the origin-destination data type can increase the model's explanatory power by determining if the coefficients of explanatory variables such as GDP and population differ for origin and destination.

This study indicates that the PPML estimator, one of the gravity model estimation approaches, outperforms the OLS-based techniques in the literature in forecasting Turkey's total annual international air cargo traffic in 2012 and 2020. As a result, the MAPE value indicates that the model developed with the PPML estimator has an average error margin of 5.88 % in predicting real cargo traffic. Furthermore, Theil U1 statistics demonstrate that the PPML estimator has nearly flawless prediction and forecast performance among the three alternative approaches.

When it comes to the prediction of total international cargo traffic on a city basis, the PPML estimator has an error margin of 48.66% on average in Istanbul, where the amount of cargo carried is relatively high, it makes an average of 200% error estimation in airports where the annual amount of cargo carried is limited, for example, Kayseri Airport. However, the OLS* approach shows almost better performance than the PPML estimator for Kayseri Airport. For example, while the OLS* approach has an average of 200% prediction error in Istanbul, this error averages down to 75% in airports with relatively low cargo traffic. On the other hand, the difference between fitted values and actual values obta ined from the estimation of the OLS estimator of the gravity model is around 150% for all aerodromes analyzed on average. This situation shows that the PPML model will give better prediction/forecasting performance for airports or countries where the amount of cargo carried is relatively high. In other words, as the amount of traffic in destination pairs increases relative to other destination pairs in the dataset, the PPML predictor shows better prediction/forecasting performance; as the amount of traffic decreases relative to other destination pairs in the dataset, the OLS-based approaches (even the approach represented by OLS*) have better performance. In this situation, it would be more appropriate for policymakers to prefer the outperformed model when making decisions about demand and capacity planning at these airports or countries. In future studies, the answer to the question of how much more the amount of cargo carried in destinations compared to other destinations in the data set is suitable for the use of the PPML estimator can be examined by researchers as a new research question.

Further study should be conducted to thoroughly examine the findings utilizing other sampling and data sets. The reasons why the methodologies employed in gravity model estimates have various forecast performances in unit breakdown is an issue that should be analyzed more in the future. Lastly, in this study, air cargo data was utilized as the dependent variable. In future studies, estimators can be compared using airline passenger data, and it can be verified which approach performs best.

This study compares the prediction/forecast performances of the OLS approach, which is one of the most used approaches for basic gravity model coefficient estimations in air transport, and the PPML and OLS* approaches, which are alternatives developed due to the limitations of the OLS approach. The findings show that the coefficients obtained with the PPML estimator in the basic gravity model coefficient estimations for the destination pairs in the data set, for those who carry more cargo than the other destination pairs, have better performance than the other alternatives in terms of prediction/forecast performance. In future studies, in addition to the GDP, population, and distance variables in the basic gravity model, this study can be repeated for the augmented gravity model, which is obtained with new variables added to the model, and the prediction/forecast performances of alternative estimators can be compared.

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ORCID:

Gizem Kaya 0000-0002-6870-7219
Umut Aydın 0000-0003-4802-8793
Burç Ülengin 0000-0001-5276-8861

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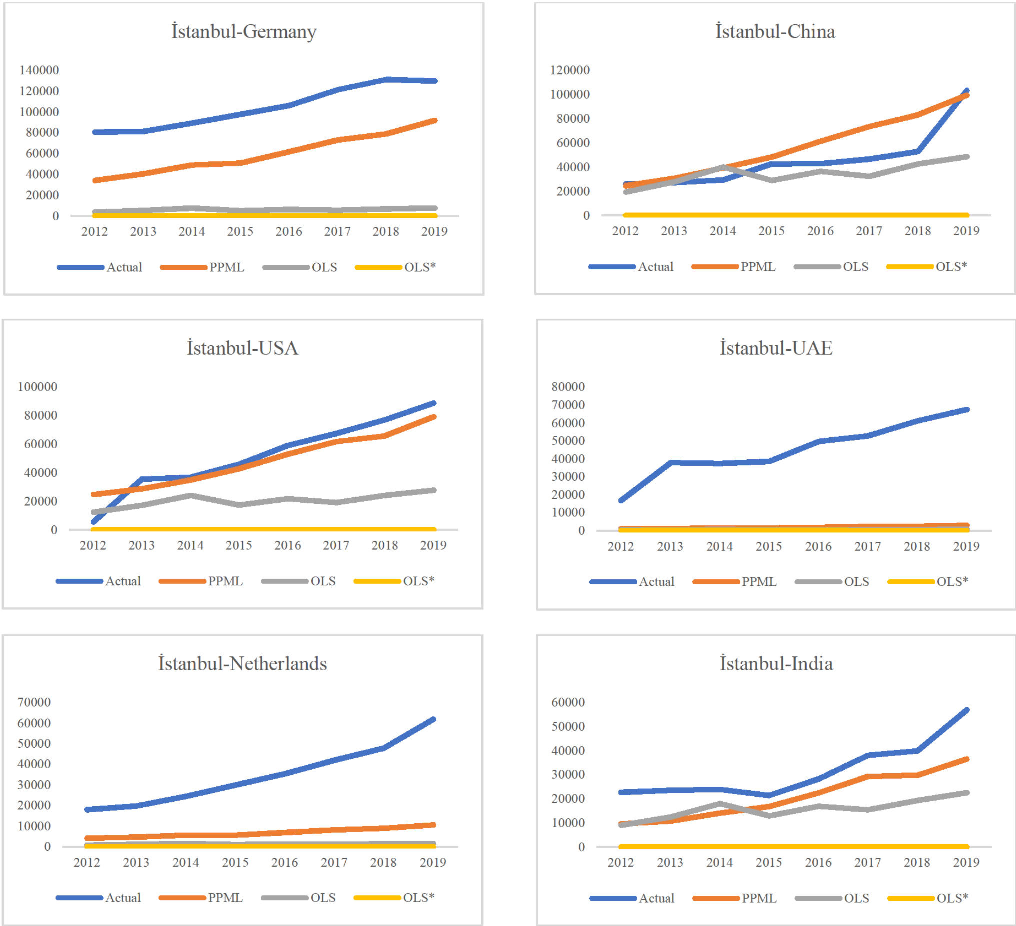
Appendix

. **Table A1:** Descriptive Statistics

Variable	Number of Observation	Mean	Standard Deviations
Total Cargo Carried (tonne)	47,771	56	1246
Distance (km)	35,827	4173	2939
Population_Arrival	49,735	1353233	2165373
Population Departure	48,951	54300000	173000000
GDP Per Capita Arrival	49,735	8216	3446
GDP Per Capita Departure	48,216	16528	21464

Airports which are included in the dataset: Adana, Adıyaman, Ağrı Ahmed-i Hani, Amasya Merzifon, Ankara Esenboğa, Antalya, Aydın Çıldır, Balıkesir, Batman, Bingöl, Bursa Yenişehir, Çanakkale, Denizli Çardak, Diyarbakır, Elazığ, Erzincan, Erzurum, Eskişehir Hasan Polatkan, Gaziantep, Hakkari Yüksekova Selahaddin Eyyubi, Hatay, Iğdır Şehit Bülent Aydın, Isparta Süleyman Demirel, İstanbul, İzmir Adnan Menderes, Kahramanmaraş, Kapadokya, Kars Harakani, Kastamonu, Kayseri, Kocaeli, Cengiz Topel, Konya, Malatya, Mardin, Muğla, Muş Sultan Alparslan, Ordu-Giresun, Samsun, Çarşamba, Siirt, Sinop, Sivas Nuri Demirağ, Şanlıurfa GAP, Şırnak Şerafettin Elçi, Tekirdağ, Çorlu Atatürk, Tokat, Trabzon, Uşak, Van Ferit Melen, Zafer.

Countries that are included in the dataset: Afghanistan, Albania, Algeria, Armenia, Austria,, Azerbaijan, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Benin, Bosnia and Herzegovina, Brazil, Bulgaria, Burkina Faso, Cambodia, Cameroon, Canada, Chad, China, Colombia, Congo, Dem. Rep, Congo, Rep., Cote d'Ivoire, Croatia, Cuba, Curacao, Cyprus (TRNC), Czech Republic, Denmark, Djibouti, Egypt, Arab Rep., Equatorial Guinea, Eritrea, Estonia, Ethiopia, Finland, France, Gabon, Gambia, The Georgia, Germany, Ghana, Greece, Guinea, Hong Kong SAR, China, Hungary, Iceland, India, Indonesia, Iran Islamic Rep., Iraq, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, Kenya, Korea Rep., Kuwait, Kyrgyz Republic, Latvia, Lebanon, Liberia, Libya, Lithuania, Luxembourg, Madagascar, Malaysia, Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Montenegro, Morocco, Nepal, Netherlands, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, Somalia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Tunisia, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United Nations Interim Administration Mission In Kosovo (UNMIK), United States, Uzbekistan, Venezuela RB, Vietnam, Yemen, Rep., Zambia.



. **Figure A1:** Comparison of the Alternative Estimators in a Country Basis

The Y axis shows cargo carried between İstanbul and Country Z (Z represents a country which has the most air cargo traffic with İstanbul in 2019 respectively);the X axis represents the year.