Journal of Air Transport Management 13 (2007) 175–183

Journal of
AIR TRANSPORT
MANAGEMENT

www.elsevier.com/locate/jairtraman

Gravity models for airline passenger volume estimation

Tobias Grosche*, Franz Rothlauf, Armin Heinzl

Department of Information Systems I, University of Mannheim, D-68131 Mannheim, Germany

Abstract

This paper presents two gravity models for the estimation of air passenger volume between city-pairs. The models include variables describing the general economic activity and geographical characteristics of city-pairs instead of variables describing air service characteristics. Thus, both models can be applied to city-pairs where currently no air service is established, historical data is not available, or for which factors describing the current service level of air transportation are not accessible or accurately predictable. One model is limited to city-pairs with airports not subject to competition from airports in the vicinity, while the other model includes all city-pairs. Booking data of flights between Germany and 28 European countries is used for calibration. Both models show a good fit to the observed data and are statistically tested and validated.

Keywords: Passenger volume estimation; Gravity model; Forecasting

1. Introduction

Demand forecasts are used by airlines to predict the travel behavior of potential passengers. Accurate forecasts are of major importance for an airline's overall success. An important element in forecasting is passenger volume estimation. The objective is to predict the number of expected passengers between two cities for a given time interval. Based on such forecasts, airlines can make decisions regarding new routes or additional flights on existing routes.

A variety of different techniques exist for passenger volume estimation. Since no single technique guarantees accuracy, airlines in fact compare forecasts from several different models. Within this set of forecasting methods, the most widely used is the gravity model.

Two gravity models for the estimation of passenger volume between city-pairs are examined here. By excluding service-related or market-specific input variables, and using cross-sectional calibration data, the models are particularly applicable to city-pairs where no air service exists, historical data is unavailable, or factors describing the current service level of air transportation are not available.

2. Air travel demand forecasting

2.1. Driving forces

In Gravity models it is assumed that air travel supports other targeted activities such as business or vacation trips (O'Connor, 1982), and that it can be derived from other selected economic or social supply variables. In general, these variables can be categorized into two groups: geo-economic and service-related factors (Rengaraju and Thamizh Arasan, 1992; Kanafani, 1983). Geo-economic factors describe the economic activities and geographical characteristics of the areas around the airports and the routes involved (Jorge-Calderón, 1997). Service-related factors are characteristics of the air transport system and are, in contrast to geo-economic factors, under the control of the airlines.

Geo-economic factors involve the economic activities and geographical characteristics of cities served by an airline. The most commonly used activity-related factors are income and the population of the metropolitan area served. A more aggregate measure can be the historical passenger volumes at each airport (Doganis, 1966). Other activity-related variables that have been used are income distribution, percentage of university degree holders, number of full-time employees, type of city, employment composition, structure of the local

*Corresponding author.
E-mail address: tobias.grosche@uni-mannheim.de (T. Grosche).

0969-6997/$ - see front matter © 2007 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jairtraman.2007.02.001

production sector, and economic, political and cultural relationships between two countries (Russon and Riley, 1993). An important geographical factor affecting inter-city air travel demand is the distance between cities. It has two conflicting effects: increasing distance leads to lower social and commercial interactions but longer distances increase the competitiveness of air transport compared to other transportation modes (Jorge-Calderón, 1997). Competition between airports in close proximity also influences demand. For example, an airport offering better schedules may attract more passengers than airports in closer proximity (Ubøe, 2004; Fotheringham, 1983b; Fotheringham and Webber, 1980).

The main service-related factors focus on the quality and the price of airline service (Jorge-Calderón, 1997). Various studies have looked at factors influencing airline service quality (Gardner Jr., 2004; Ghobrial and Kanafani, 1995; Gursoy et al., 2003; Park et al., 2004). Travel time between cities, often represented as the difference between the desired departure time of a passenger and the actual arrival time, is generally found important. Travel time partly depends on the frequency of flights offered because with increasing frequency, passengers are able to select a flight that departs closer to their preferred time. The average load factor also influences travel time as it indicates the probability of free seats at the preferred departure time. An airline's overall on-time performance is another factor as flight delays increase the travel times. Also relevant for service quality are an airline's reputation, market presence, frequent flyer membership programs, and aircraft equipment. In general, the demand for air travel decreases with increasing fares. On short-haul routes, airlines face competition of other modes that gain a relative advantage with increasing airfares (Jorge-Calderón, 1997). A survey of German passengers showed that 52% would not have traveled at all if no low-priced low-cost airline flights had been available (Tacke and Schleusener, 2003). However, some reject consideration of air fares when forecasting demand. Often, the airfare is highly correlated with the distance or travel time and is omitted to avoid issues of multicollinearity (Rengaraju and Thamizh Arasan, 1992). It may also be assumed an exogenous factor; an airline has only limited control over price in competitive markets (O'Connor, 1982). In addition, it is difficult for airlines to forecast fares reliably because determinants such as oil prices are highly volatile and hard to predict (Doganis, 2004). Finally, the use of average fares is problematic because fares often depend on route density and competition as well as on the fare classes (Lee, 2003). Jorge-Calderón (1997), for example, showed that air travel demand is price inelastic with respect to the unrestricted economy fare, and that moderately discounted restricted fares do not generate significant additional traffic.

3. Gravity model development

Gravity models were the earliest causal models developed for traffic forecasting. The gravitational law states that the gravity between two objects is directly proportional to their masses and inversely proportional to their squared distances. A simple formulation of a gravity model for human spatial interaction used for the prediction travel demand between two cities i and j is

$$V_{ij} = k \cdot \frac{(A_i A_j)^{\alpha}}{d_{ij}^{\gamma}}, \tag{1}$$

where V_{ij} is the passenger volume between i and j ($V_{ij} = V_{ij}$ and $i \neq j$), A_i and A_j are attraction factors of i and j, $d_{ij} = d_{ji}$ is the distance between the cities, and k is a constant. γ is a parameter that controls the influence of the distance on travel demand and α controls the influence of the attraction factors. Usually, the attraction and deterrence is expressed not only by a single variable but by a combination of various factors. This undirected gravity model can be extended to a directed model if V_{ij} measures directed passenger flows from i to j. Then, separate variables represent travel production (push) factors P_i^{β} the originating city and travel attraction (pull) factors A_i^{α} of the destination city. This distinction is sometimes only made by allowing the variables to have different parameter values for the origin and destination city while using the same variables for both.

Parameters are calibrated to lead to the most accurate prediction of the expected travel demand (the difference between predicted and observed travel demand should be low). Thus, data including historical passenger demand as well as characteristics of the influencing factors is used. Because accurate values for unconstrained demand can only be obtained by extensive and detailed market research, most models are calibrated using traffic figures as a substitute for the unconstrained demand. These figures, however, are influenced by the available aircraft capacity of the airlines on the routes involved, and thus only approximate unconstrained demand. In most cases, the calibration involves ordinary-least-squares methods. Table 1 offers some results from previous work.

4. Gravity models

Two new gravity models are developed for passenger volume estimation. The first (BM) minimizes the effects of competing destinations by excluding city-pairs involving multi-airport cities such as London or Berlin. The second (EM) is an extension of the BM that includes multi-airport locations using the independent variables of the BM and additional variables that describe effects of competing airports. Because both models primarily deploy geo-economic variables as inputs, and cross-sectional data for calibration, they can be used for the estimation of air passenger volume in new markets. A second motivation for using only geo-economic variables is that the airline industry is facing a more flexible business environment with volatility in competition, changes in alliances, different business models, volatile fuel prices, etc.

Table 1
Properties of selected previously estimated gravity models

Study	Factors	Obs.	R^2
Doganis (1966)	Observed passenger number at airports, distance	22	0.740[a]
Brown and Watkins (1968)	Income, sales competition, average fare per mile, journey time per mile, number of stops, distance, phone calls, international passengers on domestic flight, competition index	300	0.870
Verleger (1972)	Income, price, phone calls, distance, flying time	441	0.720[b]
Moore and Soliman (1981)	population on city-level, income, economy fare	69	0.370
	Population of airport catchment regions, income, airport catchment, economy fare	58	0.810
Fotheringham (1983b)	attractiveness/population, traffic outflow of origin, distance	9900	0.730; 0.760[c]
Rengaraju and Thamizh Arasan (1992)	Population, percentage of employees, university degree holders, big-city proximity factor, travel time ratio (travel time by rail divided by travel time by air), distance, frequency of service	40	0.952
Russon and Riley (1993)	Income, population, highway miles distance, number of jet/propeller nonstop/connection flights, driving time minus connection flight time, distance to competing airports, political state boundary	391	0.992
O'Kelly et al. (1995)	Nodal attraction, distance	294	0.850[d]
Jorge-Calderón (1997)	Population, income, proximity of hub airport, hub airport, distance, existence of body of water between cities	339	0.371
	Additional variables: tourism destination, frequency, aircraft size, economy fare (not/moderately/highly discounted restricted)	339	0.722
Shen (2004)	Nodal attraction, impedance	600	0.568[e]
Doganis (2004)	Scheduled passenger traffic at airports, economy fare, frequency	47	0.941

[a]This value is the "rank coefficient". The city-pairs are ranked according to the actual and estimated passenger volumes and the correlation between the ranks yields the rank coefficient.
[b]The study is based on the model from Brown and Watkins (1968).
[c]The model with the higher R^2 includes the "accessibility" of a destination to all other destinations of an origin" as an additional variable to consider the effects of spatial structure.
[d]Different methods for a reverse calibration of the gravity model were used.
[e]The focus is on an algebraic approach for reverse-fitting of the gravity model. Therefore, the nodal attraction is estimated endogenously from exogenous spatial interaction and impedance.

Therefore, the selection of service-related factors that are subject to continual change often play a minor role in long-term forecasting. In addition, airline-specific variables such as available aircraft, overall capacities and airport facilities are excluded because the output of the models is the number of passengers which is the basis for developing airline-specific schedules.

Market Information Data Tapes (MIDT) bookings are used as a substitute for the unconstrained demand for calibration. The data sets describe travel itineraries between airports in Germany and 28 European countries between January and August 2004. City-pairs for which data is unavailable are excluded. To reduce the effects of competing modes, only medium and long-haul routes are considered (distances greater than 500 km) as are only traffic routes with at least 500 passengers over the time period. Typical tourist routes or destinations with low-cost airlines traffic are not considered because traffic on these routes is expected to depend on different factors to routes with significant amounts of business traffic (Jorge-Calderón, 1997). The sample contains 1228 city-pairs with 137 embracing cities, and 9,091,082 passengers.

4.1. Basic gravity model

The basic gravity model is

$$V_{ij} = e^{\varepsilon} P_{ij}^{\pi} C_{ij}^{\chi} B_{ij}^{\beta} G_{ij}^{\gamma} D_{ij}^{\delta} T_{ij}^{\tau}, \quad (2)$$

where V_{ij} is total passenger volume between cities i and j. Table 2 lists the functional forms of the independent variables.

- *Population*: City populations are based on data from the statistical offices of the countries where they are located. The latest figures were always considered. Population

Table 2
Independent variables used in the basic model

Notation	Functional form	Factor
P_{ij}	P_iP_j	Population
C_{ij}	C_iC_j	Catchment
B_{ij}	B_i+B_j	Buying power index
G_{ij}	G_iG_j	Gross domestic product
D_{ij}		Geographical distance
T_{ij}		Average travel time

refers only to the city where each airport is located with potential passengers from an airport's vicinity included its catchment data.

- *Catchment*: A catchment area covers the vicinity of an airport. Usually it includes only those areas that are within a certain driving time of an airport (60 minutes). The data is derived from population data of the regions at the NUTS3-level for 2003.[1]
- *Buying power index*: The average buying power index is based on an airport's catchment area and is given at the NUTS3-level with 100 as the European average. The index is an indicator for the size of the travel budget of the population within an airport's catchment in 2003.
- *Gross domestic product*: The gross domestic product of the country of the airport is given at market prices in € millions for 2003. Because data on income distribution is not available, the GDP is considered as a representative variable for the level of economic activity.
- *Geographical distance*: The distance between two airports is the great circle distance in kilometers between their coordinates.
- *Average travel time*: The travel time is calculated from the MIDT-bookings and averages non-stop and connecting flights for each city-pair.

Distance and the travel time are expected to be deterrent factors for air travel; airfare is omitted because appropriate data is unavailable. Excluding tourist routes and destinations of low-cost airlines reduces the effect of not including fares because the remaining routes are expected to have a high proportion of business travelers who are largely time-sensitive and price-insensitive. The model's parameters are calibrated using ordinary least squares (Table 3).

The results indicate that the model is statistically valid. The null hypothesis that the independent variables have no effect can be rejected for each variable at the 1%-level and the significance of the combination of all coefficients is high, exceeding the critical F-statistics value at the 1%-level. Tests for multicollinearity produce contradictory results. The maximum variance inflation factor indicates collinearity but the maximum correlation coefficient between any two independent variables is 0.700 for distance and travel time. However, omitting one of these variables would substantially reduce the model fit. As the goal is to obtain a reliable estimation of the passenger volume, both variables were included.

The results of the statistical tests use the information available within the sample to test specific hypothesized values of individual regression coefficients (Huang, 1970). However, it is important to study model validity by testing its structural stability after calibration and a test requiring additional observations not already considered is used. Because additional observations are not available, we split the total sample into sub-samples. For the sub-samples, the stability of the input coefficients and the coefficient of determination are analyzed. The separation into subsets is conducted through two experimental setups.

For the first experimental setup (setup 1), the sample is split into two subsets of equal size (Rengaraju and Thamizh Arasan, 1992). Five experiments are conducted each with two different subsets. In the first, observations are assigned randomly to one of the subsets and in the other the observations are split into two subsets with one subset having 50% of the observations with the highest value of the selection criteria: distance, aggregate population, aggregate catchment, and observed passenger volume. For each of the experiments, one subset is used to calibrate the coefficients of the gravity model using regression analysis—the calibration sample (CS). Then coefficients obtained from the CS are used to estimate the passenger volume for the observations of the other subset (estimation sample ES), and vice versa. The results of this validation setup are presented in Table 4.

In the second experimental setup (setup 2), subsets are constructed by building successive intervals with respect to the different selection criteria used in the first experimental setup leading to subsets with different numbers of observations (Table 5).

A formal procedure to test the stability of the set of coefficients in a regression equation for different subsets is presented by Huang (1970). s is defined as the number of subsamples, β_i as the coefficients of the ith subsample ($i \in \{1,\ldots,s\}$), and β^* as the coefficients of the complete sample. The following hypotheses are tested:

$$H_0:\ \beta_1 = \beta_2 = \cdots = \beta_s (= \beta^*), \tag{3}$$

$$H_1:\ \beta_1 \neq \beta_2 \neq \cdots = \beta_s. \tag{4}$$

SSR^* is the sum of the squared residuals for the complete sample and SSR_s is the sum of the squared residuals of subsample s. The following variables are constructed:

$$Q_1 = \mathrm{SSR}^*, \tag{5}$$

$$Q_2 = \sum_s \mathrm{SSR}_s, \tag{6}$$

$$Q_3 = Q_1 - Q_2, \tag{7}$$

where n is the number of observations and v is the number of independent variables including the constant term.

[1]Nomenclature des unités territoriales statistiques (NUTS) are levels of territory of about the same population size that provide the basis for regional statistics of the European Union.

Table 3
Calibration results of the basic model

Model	Obs.	Coefficients						R^2	F
		P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}		
BM	956	0.156	0.164	1.452	−0.065	2.085	−3.297	0.761	503.4
		−7.254	−9.340	−9.023	(−3.276)	−28.592	(−41.103)		
		[0.132]	[0.201]	[0.161]	[−0.075]	[0.692]	[−1.018]		

Table 4
Validation results for the BM, setup 1

Selection criteria	Coefficients						F	R^2 (CS)	R^2 (ES)
	P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}			
BM	0.156	0.164	1.452	−0.065	2.085	−3.297	503.4	0.761	
Random	0.158	0.120	1.284	−0.053	2.047	−3.299	258.3	0.767	0.752
	0.153	0.205	1.633	−0.079	2.130	−3.301	247.4	0.759	0.761
Distance	0.190	0.058	1.053	0.017	1.941	−3.283	348.4	0.816	0.668
	0.104	0.239	1.783	−0.120	2.192	−3.537	186.4	0.704	0.799
Population	0.148	0.169	1.103	−0.036	1.877	−2.960	188.9	0.706	0.762
	0.138	0.118	1.719	−0.095	2.271	−3.606	263.3	0.770	0.679
Catch-ment	0.199	0.129	1.144	−0.083	1.707	−3.065	191.3	0.709	0.735
	0.077	0.129	1.497	−0.002	2.634	−3.623	256.3	0.766	0.614
Passenger volume	0.059	0.036	0.425	−0.038	0.345	−0.478	7.8	0.090	0.697
	0.155	0.172	1.255	−0.037	1.850	−2.680	227.3	0.743	0.078

Table 5
Validation results for the BM, setup 2

Selection criteria	Interval	Coefficients						F	R^2	Obs.
		P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}			
BM		0.156	0.164	1.452	−0.065	2.085	−3.297	503.4	0.761	956
Distance	500–1000 km	0.199	0.046	1.126	0.017	1.968	−3.310	347.9	0.822	460
	1000–1500 km	0.092	0.217	1.464	−0.092	2.259	−3.420	102.0	0.682	292
	>1500 km	0.114	0.271	2.127	−0.143	2.829	−3.610	89.3	0.731	204
Population	0–200Bill.	0.178	0.180	1.136	−0.059	1.861	−2.889	102.6	0.661	322
	200–400Bill	0.167	0.205	0.845	−0.063	2.115	−3.231	121.8	0.751	250
	400–600 Bill	−0.196	0.109	1.716	−0.086	1.930	−3.401	64.8	0.728	152
	600–800 Bill	1.909	0.066	2.356	−0.065	2.710	−3.823	42.3	0.791	74
	>800Bill.	0.158	0.007	1.971	−0.074	2.401	−3.894	70.1	0.736	158
Catchment	0–4 Mrd.	0.192	0.116	1.078	−0.071	1.643	−2.947	148.8	0.711	370
	4–8 Mrd.	0.151	0.084	1.014	−0.040	1.799	−3.366	92.5	0.726	216
	8–12 Mrd.	0.156	0.877	2.728	−0.133	2.341	−2.785	86.8	0.824	118
	12–16 Mrd.	0.091	−0.935	1.353	−0.016	2.930	−3.593	54.5	0.813	82
	>16 Mrd	−0.010	−0.050	1.719	0.063	3.197	−4.300	89.6	0.767	170
	500–1000	0.020	0.006	0.048	−0.008	−0.025	−0.014	0.9	0.020	284
	1000–1500	−0.006	0.013	0.052	0.010	0.045	−0.014	1.2	0.050	150
Passenger volume	1500–2000	0.017	0.014	0.183	0.007	0.065	0.021	5.1	0.254	96
	2000–2500	−0.025	−0.010	0.061	0.003	0.032	−0.038	2.5	0.223	60
	2500–3000	−0.013	−0.024	−0.094	0.013	−0.100	0.069	3.6	0.316	54
	>3000	0.180	0.235	0.957	−0.006	2.182	−2.819	123.1	0.708	312

Then, Q_1/σ^2 has a χ^2 distribution with n degrees of freedom, Q_2/σ^2 has a χ^2 distribution with n—sv degrees of freedom, and Q_3/σ^2 has a χ^2 distribution with $(s-1)v$ degrees of freedom. The test statistic for the null hypothesis is

$$F = \frac{Q_3/((s-1).v)}{Q_2/(n-s\cdot v)}, \tag{8}$$

which follows an F-distribution with $((s-1)v, n-sv)$ degrees of freedom. For example, splitting the sample according to the city-pair distances into two subsamples of equal size results in $F = 5.31$. The critical value of $F(8, 940)$ at the 1%-level is 2.51 (2.5%-level: 2.19). Therefore, the null hypothesis is not rejected. Table 6 presents all F-values for the two experimental validation setups.

To summarize, the basic gravity model was derived by testing all possible combinations of input variables and the model offering the best fit selected using as independent variables the factors population, catchment, GDP, buying power, travel time, and distance. For this model, the overall fit is comparable to results found in other studies. To eliminate the effects of competing airports, multi-airport cities were excluded from the data set reducing the number of observations to 956.

The model is statistically valid and all variables significant at the 1%-level. Tests for multicollinearity produced inconsistent results. If it exists, an interpretation of the individual coefficients and their order of magnitude would not be possible. Here, for example, the positive value for the distance runs counter to the common assumption for gravity models that distance has a negative impact on travel demand. However, because distance is correlated with travel time, the negative coefficient of travel time may be overcompensating the positive effect of distance. For forecasting, however, multicollinearity is not relevant as long as the model offers a good fit between the observations and the estimates and the collinearity is not expected to change significantly in the future.

The model is validated by testing its structural stability. With the exception of passenger volume as a selection criteria, the validation results (Table 4) show good fits for the subsamples, and for the estimation samples (ES) compared to the CS. The high correlation between the estimated and observed values for the ES indicates good explanatory power. Additional tests of structural stability (Table 5) show that the coefficients are only subject to minor variations across the different subsets. Changes of sign for some variables occur when using distance as a selection criterion in setup 1 (Table 4), and for all different selection criteria in setup 2 (Table 5). The results emphasize that the gravity models should, if possible, be applied to homogeneous data sets. However, the high coefficient of determination for all subsets and the results in Table 6 indicate broad applicability of the model.

A poor fit is found when separating the data by passenger volume that may be a result of the highly diverse observation data. However, the results are obtained ex post. When using the model for forecasting purposes (ex ante), it is not possible to use different models or coefficients for passenger volume groups because passenger volume is the subject of forecasting. Because the validation using the other selection criteria yielded good results, the presented model is meaningful.

4.2. Extended gravity model

In the basic model, multi-airport cities were not considered but are now brought into consideration. Rengaraju and Thamizh Arasan (1992), for example, include a ‘‘big-city proximity factor’’ as a dummy variable in their model to identify small cities in proximity of larger ones. Jorge-Calderón (1997) also uses dummies for airports that have a hub within a 200 km radius, and another to indicate if the airport is itself a hub; hubs being defined as the top two cities in an airline's host country where the airline carries out international services and that are among the top 20 destinations in terms

Table 6
F-test on structural stability of the BM

Model	F-value (setup 1)	F-value (setup 2)
Distance	5.31	3.53
Population	4.44	2.37
Catchment	6.98	3.98
Passenger volume	127.50	94.60

Table 7
Results of the BM including multi-airport cities

Model	Obs.	Coefficients						R^2	F
		P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}		
BM	956	0.156	0.164	1.452	−0.065	2.085	−3.297	0.761	503.4
		−7.254	−9.340	−9.023	(−3.276)	−28.592	(−41.103)		
BM	1228	0.136	0.193	1.558	−0.085	1.893	−3.082	0.713	506.8
(all cities)		−7.383	−10.858	−9.411	(−4.137)	−25.526	(−38.400)		
BM	1178	0.281	0.189	2.071	−0.102	1.846	−2.974	0.708	476.4
(agg. cities)		−14.664	−10.279	−12.242	(−4.815)	−24.223	(−35.130)		

of passenger throughput. Fotheringham (1983a) introduced a variable describing the accessibility of a destination airport as perceived by the passengers of the origin airport.

Table 7 shows results when applying the basic model to all city-pairs including multi-airport cities. The first line replicates the results of Table 3 and shows results when omitting all multi-airport cities. The second line offers results when applying the basic model to all observations without any modification. In the third line, airports of multi-airport cities are aggregated to represent only one generic airport for each city (input values are averaged among those airports).

For the extended model, additional variables that describe the competition faced by each airport are included in the basic model. Multi-airport destinations are characterized by the number of competing airports and their individual characteristics. It is assumed that the number of competing airports depends on distances between airports with airports defined as competing airports if the distance is less than a given maximum distance. The set of possible variables describing a competing airport are the independent variables of BM and these variables divided by the distance to the airport.

For the BM, the final set of additional variables, their functional form and the relevant distance $d_{\text{comp}-\max}$ is determined by testing all possible combinations of variables. The overall structure of the EM is

$$V_{ij} = e^{\varepsilon} P_{ij}^{\pi} C_{ij}^{\chi} B_{ij}^{\beta} G_{ij}^{\gamma} D_{ij}^{\delta} T_{ij}^{\tau} N_{ij}^{\upsilon} A_{ij}^{\alpha} W_{ij}^{\omega}, \quad (9)$$

where N_{ij}, A_{ij}, and W_{ij} are variables that describe the spatial characteristics.

The additional variables offering the best fits are seen in Table 8. The best results are found when considering airports within a distance of 200 km as competing airports. In contrast to other models the EM does not use variables for service levels or that are obtained by personal judgment (for example the identification of an airport as a hub or large city). The results of the EM model are presented in Table 9.

Table 8
Additional independent variables of the EM

Notation	Functional form	Factor
N_{ij}	N_iN_j	Number of competing airports
A_{ij}	A_iA_j	Average distance to competing airports
W_{ij}	W_iW_j	Number of competing airports weighted by their distance

The EM is statistically valid with all variables significant at the 1%-level. As in the BM, no clear results are obtained when testing for multicollinearity. The maximum variance inflation factor indicates no effects of collinearity. On the other hand, as in the BM, the maximum correlation between any two independent variables is 0.696 for distance and travel time.

We validate the structural stability of the model in the same way as for the BM. First, the structural stability is tested in two experimental setups. We study the coefficients and fit for different subsets of the total observation data. Table 10 presents results for EM using setup 1 while Table 11 presents results for setup 2. The results of the test on structural stability are presented in Table 12.

To summarize, like the BM, the EM is statistically valid and all variables are statistically significant. Tests on multicollinearity lead to inconsistent results. Thus, the interpretation of the individual coefficients and their order of magnitude is not possible, but the joint impact of correlating variables is not affected.

The results on structural stability of the EM follow the results of the BM. With the exception of passenger volume as a selection criteria, Table 10 indicates good fits for the subsamples, and for the estimation and calibration samples. The coefficients are subject to minor variations across the different subsets (Table 11). The formal test on structural stability produced the same results as for the BM (Table 12) and indicate a broad applicability of the model at the 2.5%-level for all subsets, and at the 1%-level for all subsets excluding population.

5. Conclusions

This paper presents two gravity models that can be used for air passenger volume forecasting between city-pairs. Both models use mainly geo-economic variables as independent factors. Traditionally, service-related factors or additional variables such as passenger income, are used

Table 9
Calibration results of the EM

Model	Obs.	Coefficients									R^2	F
		P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}	N_{ij}	A_{ij}	W_{ij}		
EM	1228	0.154 −7.562 [0.146]	0.224 −12.170 [0.265]	1.856 −11.099 [0.231]	−0.089 (−4.457) [−0.100]	1.804 −24.158 [0.562]	−3.032 (−38.503) [−0.912]	−0.704 (−7.825) [−0.180]	−1.141 (−4.575) [−0.088]	0.181 −7.250 [0.155]	0.730	366.2

Table 10
Validation results of the EM, setup 1

Selection criteria	Coefficients									F	R^2 (CS)	R^2 (ES)
	P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}	N_{ij}	A_{ij}	W_{ij}			
EM	0.154	0.224	1.856	−0.089	1.804	−3.032	−0.704	−1.141	0.181	366.2	0.730	
	0.164	0.198	1.560	−0.077	1.790	−3.167	−0.504	−1.004	0.148	180.4	0.729	0.677
Random	0.142	0.251	2.162	−0.103	1.837	−2.912	−0.926	−1.349	0.212	185.9	0.735	0.658
	0.191	0.120	1.488	0.006	2.068	−3.160	−0.501	−1.105	0.057	250.6	0.789	0.521
Distance	0.108	0.285	2.098	−0.154	1.674	−2.890	−0.671	−0.761	0.254	129.1	0.658	0.750
	0.090	0.245	1.538	−0.061	1.749	−2.792	−0.716	−0.716	0.169	156.3	0.700	0.630
Population	0.144	0.160	2.311	−0.135	1.842	−3.229	−0.590	−1.056	0.168	157.2	0.701	0.618
	0.234	0.136	1.384	−0.088	1.394	−2.638	−0.497	−0.758	0.221	129.8	0.659	0.644
Catchment	0.073	0.327	1.833	−0.038	2.236	−3.349	-1.137	−2.367	0.220	185.5	0.734	0.618
	0.040	0.071	0.629	−0.048	0.293	−0.405	−0.395	−0.367	0.103	10.2	0.131	0.410
Passenger volume	0.167	0.207	1.661	−0.054	1.679	−2.535	−0.298	−0.687	0.106	178.9	0.727	0.057

Table 11
Validation results of the EM, setup 2

Selection criteria	Interval	Coefficients									F	R^2	Obs.
		P_{ij}	C_{ij}	B_{ij}	G_{ij}	D_{ij}	T_{ij}	N_{ij}	A_{ij}	W_{ij}			
EM		0.154	0.224	1.856	−0.089	1.804	−3.032	−0.704	−1.141	0.181	366.2	0.730	1228
Distance	500–00	0.197	0.117	1.851	0.001	2.031	−3.160	−0.466	−1.150	0.058	251.8	0.788	618
	1000–1500	0.083	0.251	2.225	−0.138	1.757	−2.918	−0.472	−0.434	0.191	72.6	0.641	376
	1500	0.123	0.316	1.796	−0.168	1.995	−3.007	−0.930	−1.061	0.324	56.5	0.694	234
Population	0–200 Bill.	0.141	0.238	1.320	−0.074	1.873	−2.813	−0.560	−0.252	0.120	72.4	0.668	334
	200–400 Bill.	0.071	0.283	1.951	−0.043	1.698	−2.837	−0.882	−0.810	0.166	75.8	0.714	284
	400–600 Bill.	−0.494	0.084	2.154	−0.090	2.255	−3.419	0.212	−0.339	0.043	55.1	0.749	176
	600–800 Bill.	−0.049	0.247	1.294	−0.059	2.467	−3.812	−1.279	−1.078	0.161	52.9	0.832	106
	>800 Bill.	0.148	0.171	1.467	−0.165	1.388	−2.889	−0.808	−1.276	0.175	62.3	0.638	328
Catchment	0−4 Mrd.	0.234	0.161	1.406	−0.107	1.380	−2.580	−0.537	−0.910	0.207	101.8	0.677	446
	4–8 Mrd.	0.184	0.270	4.755	−0.057	1.635	−2.967	−0.566	−0.843	0.207	68.1	0.694	280
	8−12 Mrd.	0.125	1.188	2.797	−0.075	1.926	−2.790	−1.240	−3.163	0.225	64.2	0.796	158
	12–16 Mrd.	0.054	−0.130	5.613	−0.112	2.408	−2.911	−0.582	−0.394	0.414	21.4	0.702	92
	>16 Mrd.	−0.016	0.404	2.020	0.047	3.094	−4.124	−1.437	−3.887	0.259	72.6	0.730	252
	500–1000	0.022	0.012	−0.003	−0.005	−0.043	0.020	−0.093	0.049	0.036	1.9	0.048	340
	1000–1500	−0.007	0.023	0.114	0.002	0.091	−0.102	−0.013	−0.099	0.017	2.6	0.121	182
Passenger volume	1500–2000	0.006	0.027	−0.018	−0.005	0.031	0.070	−0.050	0.050	0.003	2.9	0.202	112
	2000–2500	−0.002	−0.017	0.258	0.014	0.109	−0.201	−0.033	−0.206	−0.009	3.2	0.284	82
	2500–3000	−0.005	−0.028	0.148	0.016	−0.147	0.113	−0.021	0.034	0.016	4.1	0.414	62
	>3000	0.201	0.273	5.824	−0.038	1.732	−2.325	−0.369	−0.821	0.158	96.9	0.665	450

Table 12
F-test on structural stability of the EM

Model	F-value (setup 1)	F-value (setup 2)
Distance	7.37	4.07
Population	3.55	2.06
Catchment	6.49	3.66
Passenger volume	143.13	73.17

in explanatory modeling but in new markets usually no service-related factors are available and an alternative is needed. This has been done here.

References

Brown, S., Watkins, W.S., 1968. The demand for air travel. A regression study of time series and cross-sectional data in the US domestic market. Highway Research Record, 21–34.

Doganis, R., 1966. Traffic forecasting and the gravity model. Flight International, 547–549.

Doganis, R., 2004. Flying Off Course—The Economics of International Airlines, Third ed. Routledge, London, New York.

Fotheringham, A.S., 1983a. A new set of spatial-interaction models the theory of competing destinations. Environment and Planning A15, 15–36.

Fotheringham, A.S., 1983b. Some theoretical aspects of destination choice and their relevance to production-constrained gravity models. Environment and Planning A15, 1121–1132.

Fotheringham, A.S., Webber, M.J., 1980. Spatial structure and the parameters of spatial interaction models. Geographical Analysis 12, 33–46.

Gardner Jr., E.S., 2004. Dimensional analysis of airline quality. Interfaces 34, 272–279.

Ghobrial, A.A., Kanafani, A., 1995. Quality-of-service model of intercity air-travel demand. Journal of Transportation Engineering 121 (2), 135–140.

Gursoy, D., Chen, M.-H., Kim, H.J., 2003. The US airlines relative positioning based on attributes of service quality. Tourism Management 26, 57–67.

Huang, D.S., 1970. Regression and Econometric Methods. Wiley, New York.

Jorge-Calderón, J.D., 1997. A demand model for scheduled airline services on international European routes. Journal of Air Transport Management 3, 23–35.

Kanafani, A., 1983. Transportation Demand Analysis. McGraw-Hill, New York.

Lee, D., 2003. Concentration and price trends in the US domestic airline industry, 1990–2000. Journal of Air Transport Management 9, 91–101.

Moore, O.E., Soliman, A.H., 1981. Airport catchment areas and air passenger demand. Transportation Engineering Journal of ASCE 107, 569–579.

O'Connor, W.E., 1982. An Introduction to Airline Economics, Third ed. Praeger, New York.

O'Kelly, M.E., Song, W., Shen, G., 1995. New estimates of gravitational attraction by linear programming. Geographical Analysis 27, 271–285.

Park, J.-W., Robertson, R., Wu, C.-L., 2004. The effect of airline service quality on passengers' behavioural intentions: a Korean case study. Journal of Air Transport Management 10, 435–439.

Rengaraju, V.R., Thamizh Arasan, V., 1992. Modeling for air travel demand. Journal of Transportation Engineering 118, 371–380.

Russon, M.G., Riley, N.F., 1993. Airport substitution in a short haul model of air transportation. International Journal of Transportation Economics 20, 157–173.

Shen, G., 2004. Reverse-fitting the gravity model to inter-city airline passenger flows by an algebraic simplification. Journal of Transport Geography 12, 219–234.

Tacke, G., Schleusener, M., 2003. Bargain airline pricing—how should the majors respond? Travel and Tourism White Paper Series, Simon, Kucher and Partners, Bonn.

Ubøe, J., 2004. Aggregation of gravity models for journeys to work. Environment and Planning 36, 715–729.

Verleger Jr., P.K., 1972. Model for the demand for air transportation. Bell Journals of Economics and Management Science 3.