A gravity model for estimating passenger origin-destination flows between countries worldwide

Dr. Marc C. Gelhausen
Dr. Peter Berster
German Aerospace Center (DLR)
Air Transport and Airport Research
Linder Höhe
51147 Cologne, Germany

Phone: +49 2203 601 2463
Fax: +49 2203 601 1 2463
E-Mail: Marc.Gelhausen@dlr.de

Abstract

The purpose of this paper is to present a gravity model for estimating passenger origin-destination (OD) flows between countries worldwide. These model results can subsequently serve as input to identify airport-airport OD passenger flows.

Based on data from Sabre MI and the World Development Indicators we compare gravity models estimated in a log-linearized form by traditional Ordinary Least Squares (OLS) and in a multiplicative form by Poisson pseudo-maximum-likelihood (PPML). The dependent variable to be modelled is the number of OD passengers per year between two countries. Independent variables include factors such as GDP per capita, population and air fares.

We expect to find a significant relationship between the annual OD passengers between two countries and the explanatory variables. While distance- and GDP-related variables are rather common in gravity models, we expect further insight by inclusion of the air fare variable, which has been computed on basis of Sabre MI data. Furthermore, we expect the PPML estimator to produce better estimation results than OLS.

The main contribution of this paper is a global OD passenger model on country level. We have included the fare variable to gain further insight into the structure of global passenger OD flows between countries. Furthermore, we have employed a PPML estimator to produce better and more reliable forecast results.

Keywords: Gravity model, Passenger OD demand, Pseudo-maximum-likelihood estimator

Classification: Air transport demand, Airline network development

1. Introduction

The purpose of this paper is to present a gravity model for estimating passenger origin-destination (OD) flows between countries worldwide. These model results can subsequently serve as input to identify airport-airport OD passenger flows.

There have been many applications of the gravity model to explain regional or economic phenomena. Obtaining consistent estimators of the model coefficients of the gravity model has always been an issue (see Goldberger, 1968; Manning & Mullahy, 2001); nevertheless, in many cases ordinary least squares (OLS) has been employed to obtain coefficient estimators of a log-linearized version of the gravity model. However, due to Jensen's inequality $E(\ln y) \neq \ln E(y)$, i.e. the expected value of the logarithm of a variable is different from the logarithm of its expected value (Silva & Tenreyro, 2006). Thus, estimated model coefficients are biased if the gravity model is estimated via OLS in its log-linearized form, unless the error term has certain distributional properties which are in most cases very unlikely to hold. For example, as a result the estimated distance coefficient of a gravity model is typically too low (Siliverstovs & Schumacher, 2009). In connection with air travel, this leads e.g. to an underestimation of international long-distance travel. On the other hand, Silva & Tenreyro (2006) propose a pseudo-maximum likelihood (PPML) estimator based on a Poisson distributed error term to obtain unbiased coefficient estimates of the gravity model. Here, the model is estimated in its original multiplicative form.

The paper is structured as follows: Chapter 2 gives a brief overview of gravity models for OD demand of air passengers (Gelhausen et al., 2017). Chapter 3 describes the data that has been employed for estimation of an OD air passenger model based on an OLS and Poisson pseudo-maximum likelihood estimator (PPML). Chapter 4 covers the core of the paper, i.e. model estimation and a comparison of the OLS vs. the PPML estimator based on a data set that has not been used for model estimation. The paper also includes a sample forecast for 2035 based on population forecasts from the UN and GDP forecasts from the OECD. Furthermore, we compare the results that traditional OLS and PPQML produce. Finally, the paper concludes with a brief summary and some conclusions.

2. Literature review

To date, the gravity model has been employed in a wide range of disciplines, e.g. in regional science (e.g. Mikkonen & Luoma, 1999), transportation (e.g. Evans, 1976) and trade (e.g. Bergstrand, 1985; Linnemann, 1966 and Tinbergen, 1962). One of the first gravity models employed in air transport research was developed by Harvey (1951) to analyse airline traffic patterns in the USA. An overview of selected gravity models in air transport research can be found in Grosche et al. (2007) and in Tusi & Fung (2016). In particular, the scope of work of Grosche et al. (2007) has some common ground with this work: They present two gravity models to estimate the air passenger volume of city pairs without an air service currently existing. Looking at the bigger picture, the gravity model has been applied to many different research objects in air transport research: e.g., Tusi & Fung (2016) analysed passenger flows at Hong Kong International Airport (HKIA) and focused their research work more on a single airport, whereas Matsumoto (2004) and Shen (2004) based their gravity models more on a network analysis. Matsumoto (2004) estimated a gravity model for passenger and cargo flows between a distinct number of large conurbations like Tokyo, London, Paris and New York. Shen (2004) estimated a gravity model to analyse inter-city airline passenger flows in a 25-node US-network. Bhadra & Kee (2008) employed a gravity model to analyse demand characteristics, i.e. fare and income elasticities of the US OD market over time. Endo (2007) developed a gravity model to analyse the impact of the bilateral aviation policy between the USA and Japan on passenger air transport. Hazledine (2009) estimated a gravity model to analyse border effects in international air travel.

Table 1

Selected gravity models for OD air passenger demand (Gelhausen et al., 2017)

Authors	Number of variables	R^2
Endo (2007)	4-9	43%-69%
Harvey (1987)	6	76%
Hazledine (2009)	9-11	53%-56%
Matsumoto (2004)	7-19	39%-45%
Tsui & Fung (2016)	13	74%

The gravity models listed have been estimated by traditional OLS in their log-linearized form. Table 1 displays some model in terms of their number of parameters and R^2 based on the estimation data set, if available (Gelhausen et al., 2017). If the paper comprises various models, e.g. in the case of different market segments, ranges of values are given. Number of variables and R^2 vary considerably and are determined by e.g. scope of work, problem structure and data availability. However, there are two caveats: First, R^2 is typically computed on the basis of the log-linearized model, thus underrepresenting large deviations between actuals and model output of the multiplicative form due to the nonlinear transformation of the logarithm. As a result, R^2 of the original gravity model tends to be much lower. Second, R^2 is based on the estimation data set, which does not really assess forecast efficacy. Therefore, we have chosen a different approach based on Carson et al. (2011) and Gelhausen et al. (2017) to test forecast efficacy of a model on 10% of a data sample that has not been used for parameter estimation.

3. Data

The base year of the data used for model estimation and testing is 2014. Demand data, i.e. OD volume per country pair, number of airports per country and average air fares, has been retrieved from Sabre MI (2017), while socio-economic data like GDP, population and tourism expenditures/receipts has been taken from the World Development Indicators (WDI) of the World Bank (2016). The full data set comprises of 14,642 country pairs with corresponding OD flows, of which 13,178 data sets were used for model estimation and 1464 (10%) were employed for model testing.

For the example forecast of the year 2035, economic data, i.e. the GDP forecast is retrieved from OECD (2017) and the population data forecast from the UN (2015). The Airbus Global Market Forecast (2016) and the Boeing Current Market Outlook (2016) have been taken as reference forecasts for comparison purpose. Table 2 summarizes the data that has been used to estimate and test the models and to produce the example forecast for 2035.

Table 2 displays the variables of the final model setup, both for the traditional OLS and the PPML approach. Most variables are more or less self-explanatory; however, the variables “distance” and “total air fare” need some additional explanation: Both variables represent average values between two countries, i.e. origin and destination. Raw data is on airport and airline level and retrieved from Sabre MI and is weighted by OD demand volume to obtain “average” values between two countries. While the concept of average distances and especially average air fares between two countries seems rather weird, the approach works quite well, as we can see in chapter 4.

Table 2

Data employed for model estimation, model testing and example forecast 2035 (blue: forecast data)

Variable name	Data source	Data description
Distance	Sabre MI	Weighted mean flight distance in km between countries. Weighted mean is based on airport pairs with OD demand as weights.
Total air fare	Sabre MI	Weighted mean total air fare in USD between countries. Weighted mean is based on average total air fares between airports with OD demand as weights.
National	Sabre MI	Value of 1, if it is an domestic flight, 0 otherwise.
Continental	Sabre MI	Value of 1, if it is a flight within one of the 7 world regions (Europe, Asia, Africa, North America, South America,Middle East & Southwest Pacific), 0 otherwise.
Number of airports (origin)	Sabre MI	Number of airports of the origin country.
Number of airports (destination)	Sabre MI	Number of airports of the destination country.
GDP per capita (origin)	WDI/OECD	GDP per capita in USD of the origin country.
GDP per capita (destination)	WDI/OECD	GDP per capita in USD of the destination country.
Population (origin)	WDI/UN	Number of people of the origin country.
Population (destination)	WDI/UN	Number of people of the destination country.
Tourism expenditures (origin)	WDI	Tourism expenditures in USD of the origin country.
Tourism receipts (destination)	WDI	Tourism receipts in USD of the destination country.

4. Model estimation, model testing and example forecast for 2035

Table 3 displays the estimated model coefficients, both for the OLS and the PPML approach. Except for the “continental” dummy variable in the OLS model all coefficient estimates are highly significant (p-Value < 0.01) and of the expected sign. R^2 of the OLS approach is 76.54% (based on the log-linearized version of the gravity model for coefficient estimation) and 61.66% (based on the original multiplicative version of the gravity model), respectively, and McFadden’s pseudo-R^2 of the PPML approach is 98.96%. Compared to the models of Table 1 this is a very satisfactory value of the R^2. Furthermore, Table 3 shows the sum of coefficients of GDP per capita and population (both for origin and destination), which serves as an indicator how GDP-responsive the model is. Here, the OLS model is much more GDP-responsive than the PPML approach (1.78 vs. 1.28). Before discussing the estimated elasticities of both models, we take a closer look at forecast efficacy evaluated by means of the test data set.

Table 3

Parameter estimates of the OLS and PPML approach

#	Variable	OLS Coefficient	OLS Standard error	OLS p-Value	PPML Coefficient	PPML Standard error	PPML p-Value
1	Constant	-14.70661	0.41904	0.0000	-6.75120	0.00266	0.00000
2	Distance	-0.75995	0.03486	0.0000	-0.05210	0.00017	0.00000
3	Total air fare	-1.30891	0.04147	0.0000	-1.13411	0.00022	0.00000
4	GDP per capita (origin)	0.34755	0.02887	0.0000	0.37592	0.00017	0.00000
5	GDP per capita (destination)	0.53988	0.01866	0.0000	0.27608	0.00011	0.00000
6	National	1.56150	0.17974	0.0000	0.15984	0.00056	0.00000
7	Continental	0.10257	0.06230	0.0997	0.15754	0.00022	0.00000
8	Population (origin)	0.35143	0.02377	0.0000	0.34880	0.00015	0.00000
9	Population (destination)	0.54339	0.01413	0.0000	0.27577	0.00010	0.00000
10	Tourism expenditures (origin)	0.38246	0.02397	0.0000	0.09768	0.00013	0.00000
11	Tourism receipts (destination)	0.23369	0.01338	0.0000	0.22170	0.00009	0.00000
12	Number of airports (origin)	0.25641	0.01436	0.0000	0.11569	0.00009	0.00000
13	Number of airports (destination)	0.22835	0.01443	0.0000	0.13145	0.00009	0.00000
Sum of (4,5,8 & 9)		**1.78224**			**1.27657**		

Figure 1 displays the in-sample and out-of-sample residual sum of squares (RSS) of the OLS and PPML approach. The values are very high due to the large sample sizes (especially the estimation data set) and the fact that both approaches are evaluated by means of the multiplicative form of the gravity model. For comparison: In its log-linearized form the OLS model produces a value of 36505.18 for the estimation data set. However, while the PPML model produces a significant higher value on the estimation data set it generates a much lower RRS on the test data set compared to the OLS model. This tends to favour the PPML approach in terms of out-of-sample forecast efficacy. Nevertheless, model comparison is a little tricky, since only the OLS approach is aimed at minimizing RSS on the estimation data set, while the PPML is based on maximizing the log-likelihood of the estimation data sample. Furthermore, the estimation data set contains the two largest OD flows, i.e. US and China domestic, which account for almost one third of global OD passenger demand. Thus the estimation and test data sets differ in their characteristics, e.g. mean of the data set, which sets the bar even higher for the models. However, shifting one of these flows to the test data set would reduce the efficiency of the estimators, which is rather undesirable.

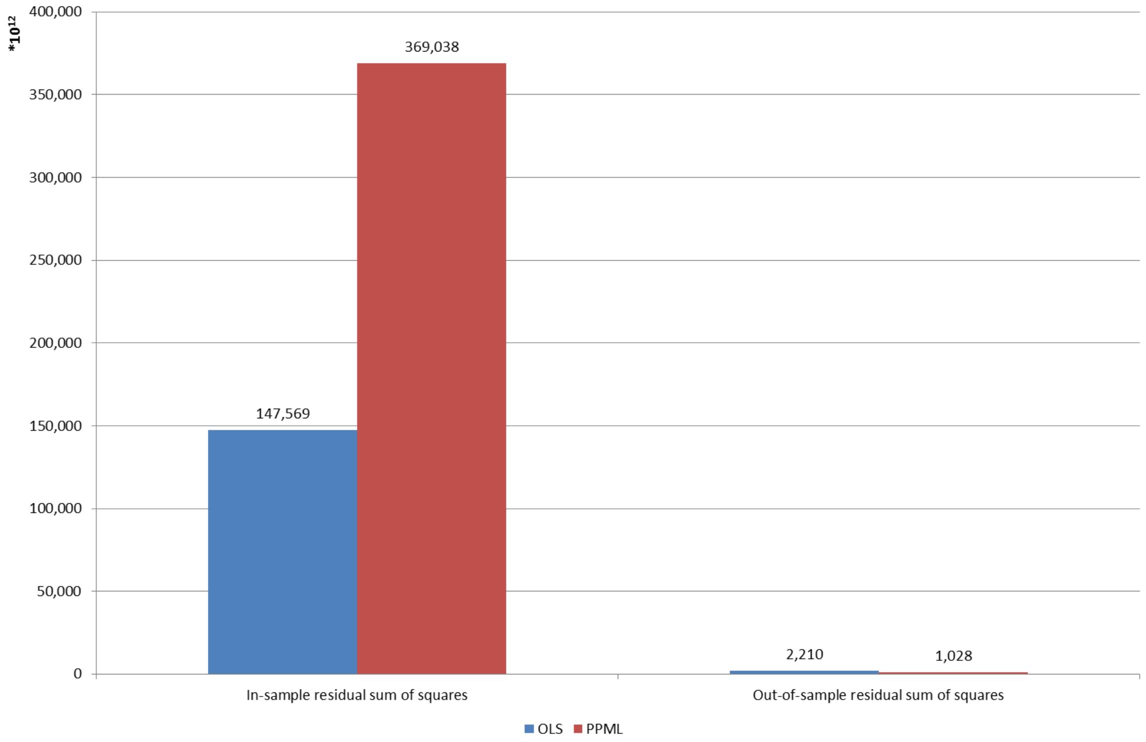

Fig. 1. Residual sum of squares of the OLS and PPML approach

Figure 2 shows the in-sample and out-of-sample standard deviation of the forecast error for both approaches and the interpretation of results is basically the same in the case of Figure 1: The PPML model produces a higher value in-sample but a significant lower value out-of-sample compared to the OLS approach. This again tends to favour the PPML approach in terms of out-of-sample forecast efficacy. For comparison purposes, in its log-linearized form the OLS model produces a value of 1.67 for the estimation data set.

Log-linearization of the dependent variable, i.e. passenger OD demand, narrows its range massively down, leading to much lower statistics, i.e. RSS and standard deviation of the forecast error, in model estimation and evaluation and a higher R^2 compared to the original multiplicative form of the gravity model.

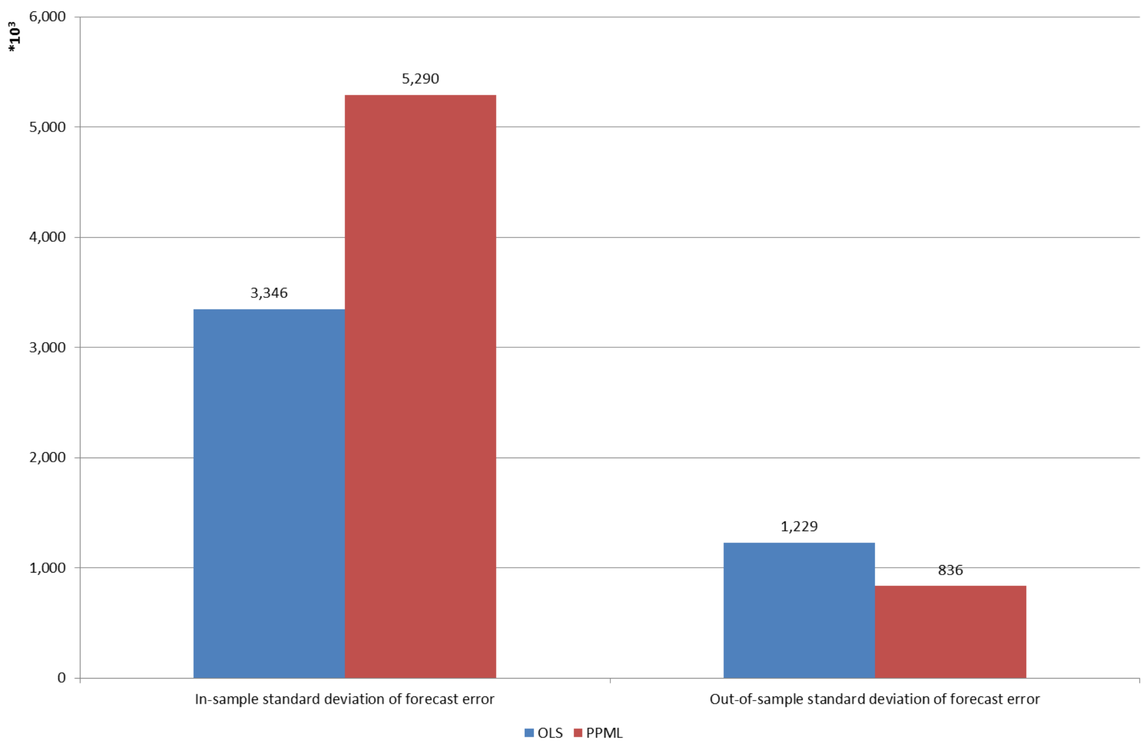

Fig. 2. Standard deviation of the forecast error

Finally, Figure 3 displays the corresponding ratios from Figures 1 and 2. As a result, we can conclude that the PPML approach has a much better out-of-sample forecast efficacy. However, compared to various models (Table 1), even the OLS model performs rather well in terms of R^2. But because of log-linearization R^2 of gravity models should be taken with a grain of salt: Forecast efficacy of the multiplicative form is typically lower than the log-linearized version suggests.

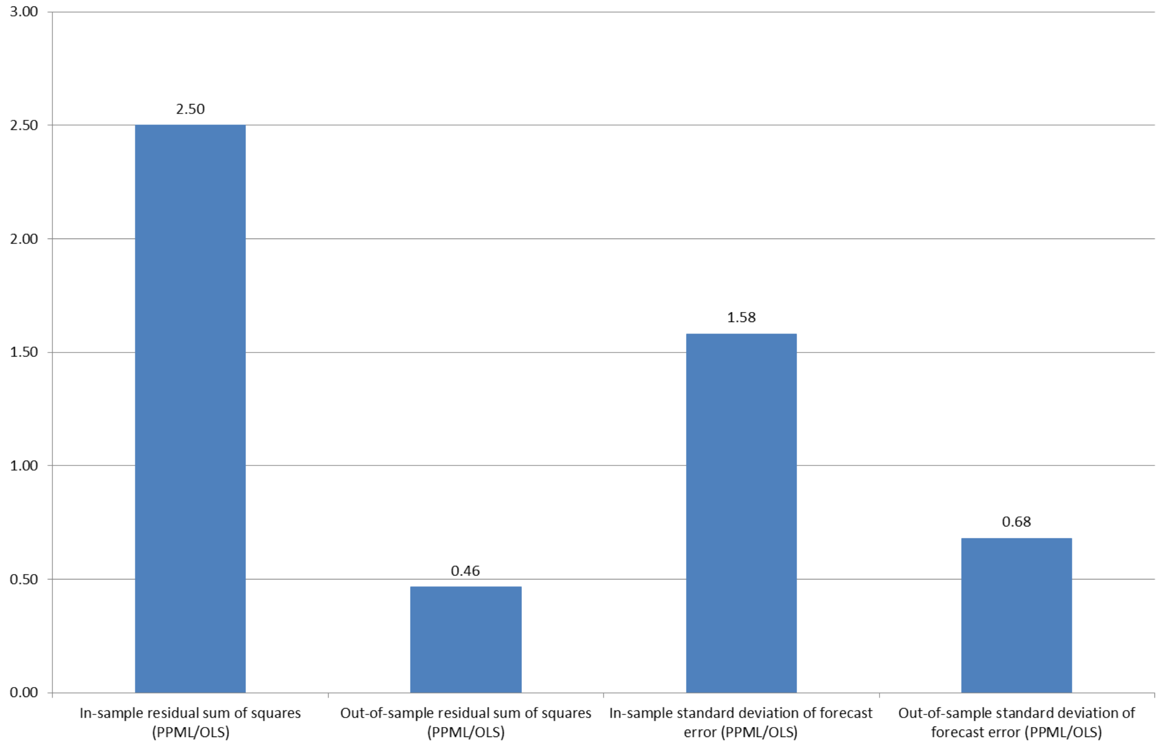

Fig. 3. Ratio of forecast efficacy evaluation statistics (PPML/OLS)

Figure 4 compares model elasticities of the OLS and PPML approach. Especially distance, but also GDP per capita and population play a bigger role in the OLS approach than in the PPML model. On the other hand, total air fare is relatively more important in the PPML approach and GDP and population elasticities are more evenly distributed. As a result, the OLS model is much more distance and GDP-responsive. Tourism receipts and expenditures and the number of airports are more important in the OLS model than the PPML approach, but their elasticities are much lower and thus play only a minor role. Furthermore, scenario analyses typically do not focus much on these factors. Here, GDP, population and air fare development usually play a much more important role.

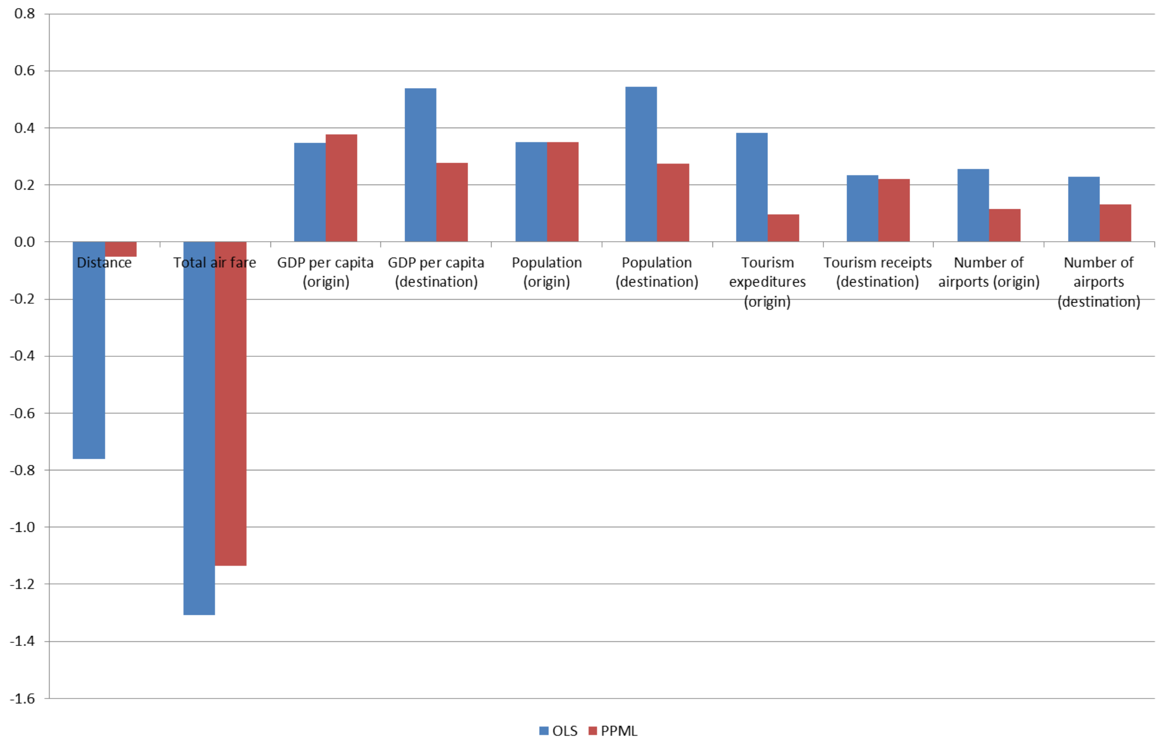

Fig. 4. Comparison of the estimated model elasticities of the OLS and PPML approach

Figure 5 compares the values of the constants and the dummy variables of the OLS and PPML approach. The absolute values of the constant and the "national" dummy variable are significantly larger in the OLS model compared to the PPML approach. We interpret these findings as follows: The OLS model penalizes increasing distance much more than the PPML approach. This is partly offset by the large absolute value of the constant and a high value of the "national" dummy variable to account for domestic traffic, especially in the US & China. Thus, the coefficient estimates of the PPML model seem to be much more balanced and this view is supported by the forecast efficacy of the model. The OLS approach seems to be more "data-fitting" because of a misspecified error component.

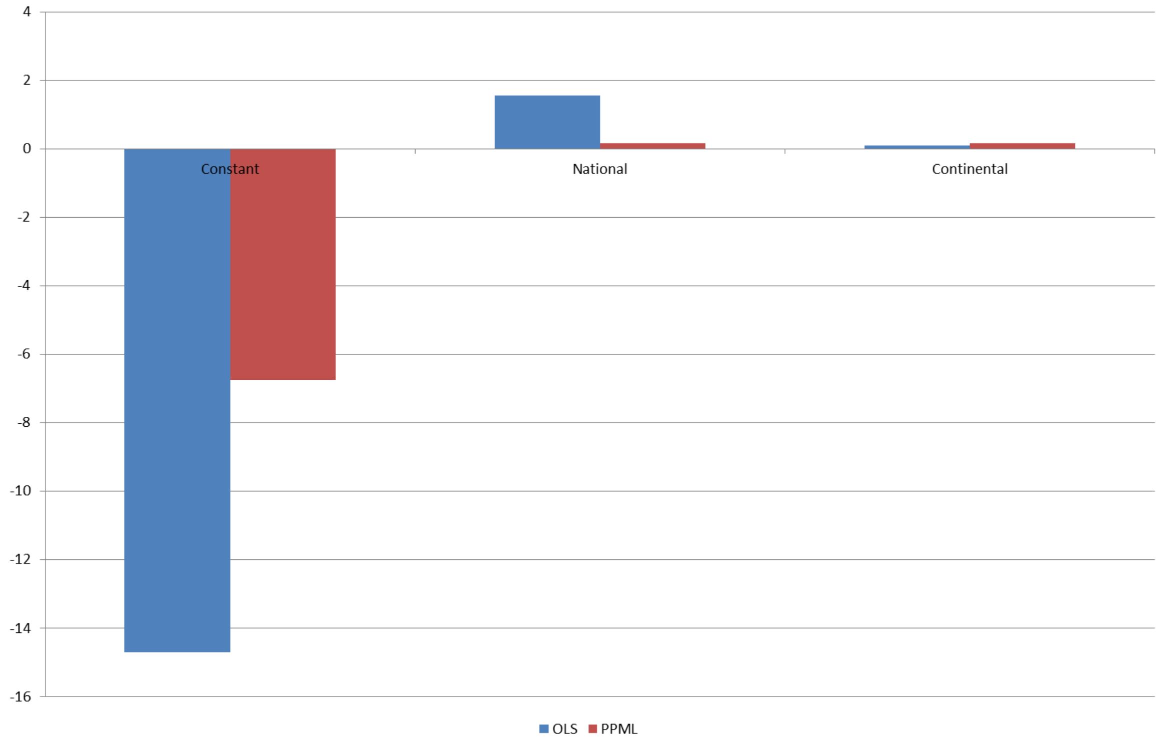

Fig. 5. Comparison of the estimated constants and dummy variables of the OLS and PPML approach

Figure 6 shows different scenarios of an example forecast of global annual OD demand for the period from 2016 to 2035. Furthermore, Figure 6 displays the annual global passenger growth forecasts of Airbus (2016) and Boeing (2016) for the period from 2016 to 2035. Although passenger numbers and OD demand are different because of transfer passengers, the Airbus and Boeing forecast serve as a first benchmark for comparison of different scenarios. Forecast values for Airbus are 4.5% p.a. and 4.0% p.a. for Boeing.

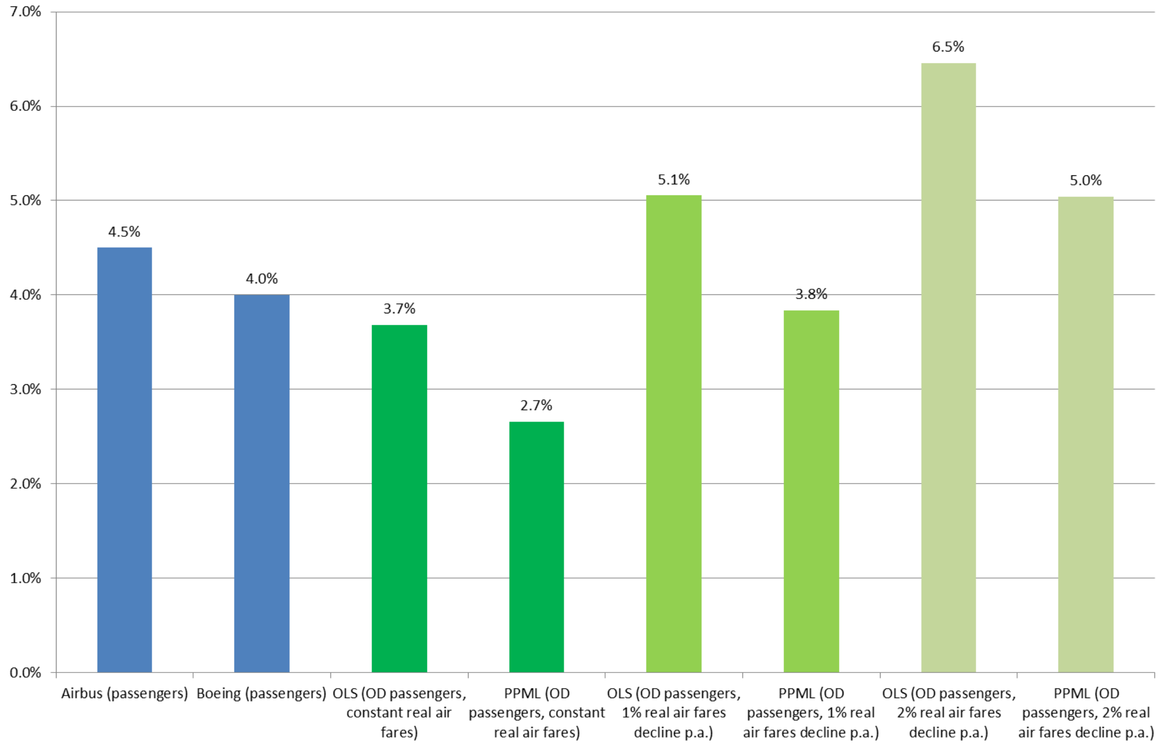

Fig. 6. Comparison of different forecast scenarios in terms of air fares development with Airbus Global Market Forecast and Boeing Current Market Outlook (Compound annual growth rate (CAGR) 2016 – 2035)

According to Sabre MI (2017) OD passengers increased between 2002 and 2016 on average by 6.1% per year (2011-2016: 9.6%) and total passengers, i.e. including transfer passengers grew on average by 5.4% per year (2011-2016: 9.1%), however, while being more volatile in recent years, the difference between these two growth rates is more or less stable over time, as Figure 7 illustrates. Furthermore, we have observed that concentration of flights on airports worldwide has more or less stagnated for a while: The Gini-coefficient is in a range of 0.81 to 0.82 for the years 2000 to 2014; nevertheless, this is still a very high degree of concentration, but varies by world region (Gelhausen and Berster, 2017). Thus, the long-term difference in average annual growth rates of OD passenger and total passenger volume is about 0.5 to 0.7 percentage points on a global scale.

Fig. 7. Comparison of annual growth rates of global OD passengers and total passengers (including transfer passengers) for the period 2003 to 2016 (Sabre MI, 2017, own calculations)

Forecast data has been retrieved from OECD (2017) for global real GDP growth from 2016 until 2035. The medium variant of the UN World Population Prospects (2015) has been chosen for a forecast of global population growth for the period from 2016 to 2035. Thus, we have taken a value of 3.2% p.a. for global GDP growth and 0.092% p.a. for global population growth. In matters of real air fares we distinguish between three scenarios:

- Constant real air fares,
- 1% decline p.a. of real air fares, and
- 2% decline p.a. of real air fares.

A long-term decline of real air fares seems plausible due to the growth of the low-cost carrier segment and legacy carrier pushing their own low-cost subsidiaries. Furthermore, there is market potential in the long-haul segment (e.g. Gelhausen et al., 2016). Even nominally stagnant air fares mean declining real air fares due to inflation.

Figure 8 shows the development of the OD average base fare in USD and the average yield in US cent per km for the period 2002 to 2016, as total air fares are only available from 2014 to 2016 (Sabre MI, 2017). Between 2002 and 2016 the nominal OD average base fare and average yield declined by 0.7% per year (CAGR). Highest nominal values for the OD average base fare and average yield were reached in 2012. For this period, CAGR was 3.6% and 3.7%, respectively. Thereafter, i.e. from 2012 to 2016, as well as the years 2009 and 2010, OD average base fare and average yield declined rapidly by 10.6% and 10.8% per year on average, respectively, accompanied by a large decline of jet fuel prices and increasing low-cost competition. The period with the largest CAGR is 2002 to 2008: Here, we find values of 4.7% and 3.5% for the OD average base fare and the average yield, respectively. While air fares are volatile over time, the long-term assumption of stagnating or slightly declining nominal air fares seems not to be unrealistic.

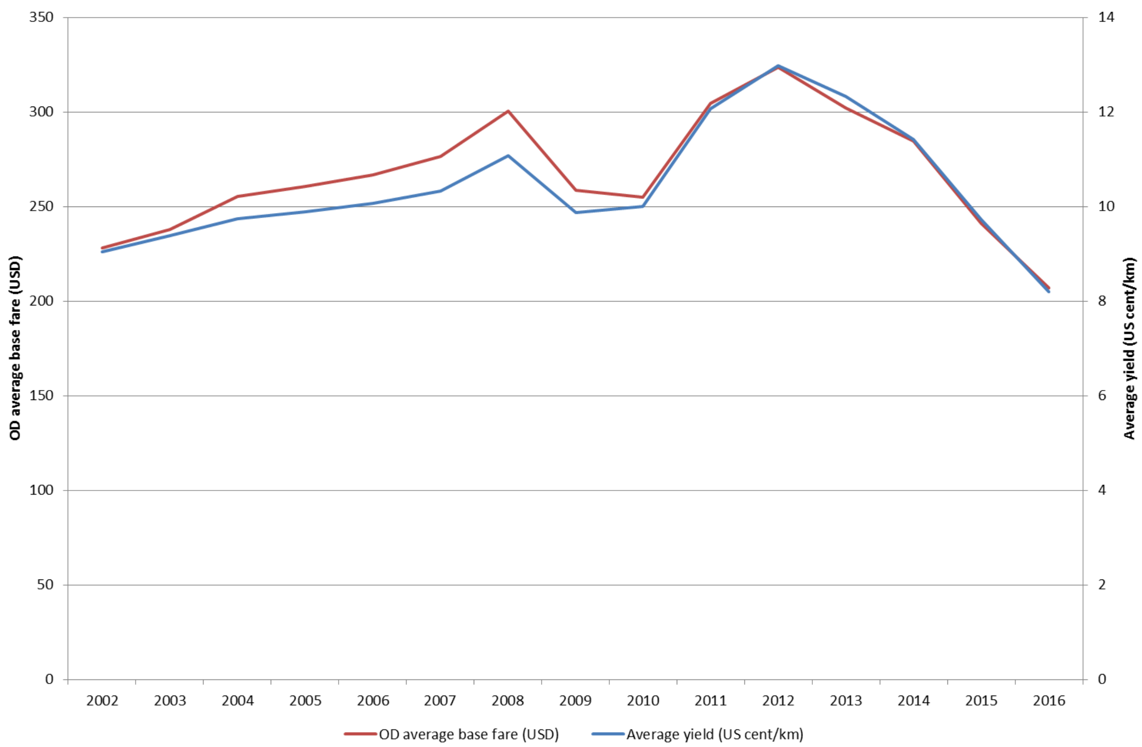

Fig. 8. Development of OD average base fare in USD and yield in US cent worldwide for the period 2002 to 2016 (Sabre MI, 2017, own calculations)

Figure 9 displays the development of US kerosene-type jet fuel retail sales by refiners in USD/Gallon and the year-to-year price changes in %. There was a large decline in 2009 and since 2012 jet fuel prices continue to decline. Furthermore, jet fuel prices and air fares are highly correlated: The value of the correlation coefficient for the data sample is 0.9, i.e. jet fuel prices and air fares move more or less in the same direction. However, while the OD average base fare and average yield declined by 0.7% per year during the period 2002 to 2016, jet fuel prices increased by 4.4% per year on average, despite large fluctuations. On the other hand, during the 2012 to 2016 period, jet fuel prices fell on average by 19% per year, while the OD average base fare declined by 11% per year. Figures 8 and 9 illustrate that jet fuel prices are much more volatile than air fares, but tend to move in the same direction.

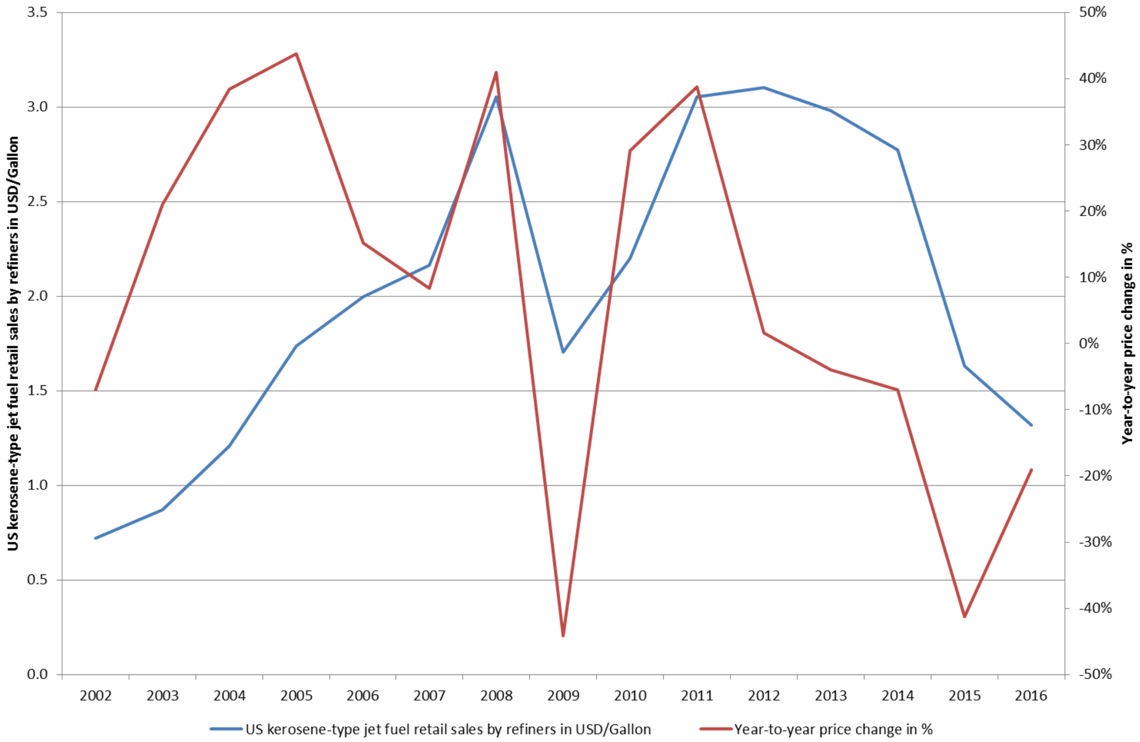

Fig. 9. Development of US kerosene-type jet fuel retail sales by refiners USD/Gallon (US Energy Information Administration, 2017, own calculations)

Against this background the scenario assumptions seem realistic: Average inflation rate of consumer prices of the Euro area was 2.2% between 1995 and 2015 and 4.4% worldwide (World Bank, 2016). However, air fares could also nominally increase, but less than the inflation rate, which also leads to a depreciation of real air fares. Still, these assumptions remain more or less arbitrary; however from our point of view a decline of real air fares is rather likely and furthermore, they primarily serve to compare the OLS and the PPML approach and not as a “real” forecast.

Depending on the scenario chosen, the OLS model produces forecast values between 3.7% p.a. for constant real air fares and 6.5% p.a. for a 2% decline of real air fares. The PPML approach produces lower forecast values which are in a range of 2.7% p.a. and 5.0% p.a. Overall, a decline of real air fares seems to be more likely than constant real air fares, especially compared to the Airbus and Boeing forecasts.

5. Summary and conclusions

The objective of the paper is to present a gravity model to forecast OD passenger demand between countries based on such factors as population, GDP per capita and air fares development. In this paper, we employ a Poisson pseudo-maximum-likelihood (PPML) estimator and compare the results with the traditional approach of log-linearization of the multiplicative gravity equation and applying ordinary least squares (OLS). The latter approach suffers in many cases from biased coefficient estimates; in particular the effect of distance on OD demand is overestimated. The models are estimated on a rather large data set, of which 10% are excluded for out-of-sample model testing and evaluation of forecast efficacy. Here, we find that the PPML approach produces far better out-of-sample forecasts and handles small OD flows which are quite common much better. On the other hand, the OLS model tends to over predict out-of-sample flows, especially small OD flows. Finally, an example forecast for the period 2016 to 2035 is presented to compare the OLS and the PPML approach and Airbus and Boeing passenger forecast. Here, we study the effect of future air fares development on OD demand and find the PPML model to be much more air fare-responsive than the OLS approach. In contrast, the latter is more GDP-responsive. While the passenger forecasts of Airbus and Boeing are not directly comparable with the forecasts of the OD models because of transfer passengers lacking, the results obtained tend to be more or less coherent. For the example forecast we assume constant or declining real air fares. This hypothesis is backed up by data of historical fare and jet fuel development as well as data on consumer price inflation. Jet fuel prices and air fares have a value of the correlation coefficient of 0.9; however, jet fuel prices are much more volatile than air fares. From this study we conclude that the PPML model is superior to the OLS model and that air fares development is very important for explaining OD demand and potentially new direct routes, while the traditional OLS approach overestimates distance and GDP effects, thus inflating small OD flows. While short- to medium-distance networks are quite matured in terms of nonstop connections, this approach could be beneficial for the identification and assessment of long-distance connections, especially for long-haul low-cost flights. The traditional OLS approach penalized distance too much and undervalues the effect of air fare reductions.

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