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Price Elasticities in Aviation: Novel Estimates from Structural Gravity Modelling and Instrumental Variables Approach

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Abstract

This paper provides updated estimates of price elasticities of air passenger demand, using a comprehensive 10-year dataset from Sabre Market Intelligence (2010–2019). It expands the scope of previous research by incorporating global demand and price data at both the country and the city level and addressing key methodological issues, such as air fare endogeneity, using econometric techniques like Two-Stage Least Squares (2SLS) and fixed effects panel data analysis.
The study reveals significant variation in price elasticity estimates, influenced by the choice of estimator, inclusion of fixed effects, and treatment of endogeneity of demand and ticket prices. While the global price elasticity is estimated at -0.87, travel originating from Europe exhibits a higher price sensitivity with an elasticity of -1.27. Moreover, medium-haul routes show a greater price elasticity than short-haul or long-haul routes. The findings offer valuable insights for policymakers to evaluate the impact of regulatory measures, for researchers to understand the cost sensitivity of demand for new technologies, and for airlines to optimize pricing strategies. Ultimately, this research contributes to a better understanding of the characteristics of air transport demand and its sensitivity.

Keywords: Price elasticity; Air transport; Gravity model; Endogeneity; IV-approach

1. Introduction

Price elasticity of demand is a foundational concept in economics, quantifying the degree to which the quantity demanded of a good or service responds to changes in its price. In the aviation sector, understanding price elasticities of passenger demand is crucial for assessing how changes in ticket prices influence travel behavior (Gillen et al.,

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2007). Whereas price elasticities gained recognition in light of revenue management decisions, demand forecasting, and competition analysis, in recent years, the interplay between price elasticity and environmental regulations has gained increasing importance in the literature (Oesingmann, 2022b; Molloy et al., 2012). The European Union's Emissions Trading System (EU ETS) is an example of how environmental policies can influence airline pricing strategies and demand. By imposing costs on carbon emissions, the EU ETS encourages airlines to adopt more fuel-efficient technologies and consider alternative fuels. However, these additional costs are often passed on to passengers in the form of higher ticket prices. This raises important questions about the impact of environmental policies on current passenger demand and demand forecasts, highlighting the need to incorporate up-to-date estimates of price elasticities into the simulations.

In the aviation sector, price elasticity is not uniform, and previous research has shown that it varies significantly based on factors such as travel purpose, geographic regions, and the availability of alternative transportation options (Brons et al., 2002; Gillen et al., 2007; InterVistas 2007; Morlotti et al., 2017). Previous research on the subject is diverse, but there are limitations of existing studies. Several studies focus on a specific geographic area, often the US domestic market (Granados et al., 2012a; Mumbower et al., 2014), or analyze data from a short period of time and/or from a single airline and limited routes. Moreover, not all studies address the topic of endogeneity of airfares, which, if is inherent and not controlled for, leads to upwardly (closer to zero) biased estimates of price elasticities (Mumbower et al., 2014; Molloy et al., 2012).

To address these shortcomings, this paper makes several noteworthy contributions to the field of aviation. First, it uses a comprehensive dataset derived from Sabre Market Intelligence (MI), which includes detailed demand and price data at both the country and city level. The dataset spans 10 years (2010–2019), offering a broader and more granular perspective compared to previous studies. In addition, this paper expands the scope of analysis beyond the geographical limitations of earlier studies, including worldwide data. Second, the study addresses several methodological issues, such as the use of modern gravity modelling standards and the matter of the endogeneity of air fares. The critical issue of price endogeneity is tackled by employing advanced econometric techniques such as Two-Stage Least Squares (2SLS), panel data analysis including different fixed effects aside from using Ordinary Least Squares (OLS) and Poisson Pseudo-Maximum Likelihood (PPML). By this, the study enables to compare results derived from different estimators. Our results highlight that current estimates of price elasticity vary significantly depending on the estimator used, whether fixed effects are included, and how endogeneity is addressed, making it challenging to identify a single definitive estimate for the price elasticity of demand.

2. Literature review

The literature shows that demand changes in response to price changes are significantly influenced by several factors. First, business travelers tend to be less sensitive to price changes and more sensitive to travel time changes, which means that the demand is less elastic in terms of prices. Secondly, elasticity tends to be higher on short-haul routes because alternative modes of transport may be available for these routes. Thirdly, the level of aggregation of routes into markets or geographical regions, such as city or country, plays a role. Increasing the fare for individual routes or airlines will result in higher changes in demand. In comparison, rising fares for whole markets or countries due to, e.g., taxes imply higher prices for potential substitutes and therefore less demand shift.

Brons et al. (2002), for example, published a meta-analysis based on 39 studies, with an average elasticity value of -1.2. A second meta-analysis by Gillen et al. (2007) based on 21 studies published between 1980 and 2002 calculates a mean elasticity of -1.12, with values ranging from -3.2 to 0.04 for all estimates. Depending on travel distance and purpose, and separated for domestic and international flights, they calculate average elasticity values for leisure travelers from -1.04 to -1.52. Global applicable calculations that allow for comparing geographical and temporal aspects have been published by InterVistas (2007). They find a pan-national elasticity of -0.6, an elasticity for the national level of -0.8, and -1.4 for the market level. The authors suggest various geographical multipliers and a multiplier for short-haul, as the elasticity for shorter trips appears to be higher.

More recent studies usually apply different estimators like Ordinary Least Squares (OLS), Two-Stage Least Squares (2SLS), and non-linear estimators to compare results (Borsati and Fageda, 2024). While Granados et al.; Granados et al. (2012a; 2012b) and Mumbower et al. (2014) focus on U.S. domestic routes, Molloy et al. (2012), Morlotti et al. (2017), Boonekamp et al. (2018), and Hanson et al., 2022 analyze intra-European aviation data.

Worldwide routes are investigated by Margaretic et al. (2017) and Gelhausen et al. (2020). Elasticity estimates vary greatly from very elastic estimates of below -1 to inelastic estimates close to zero. Gelhausen et al. (2020), for example, estimate a global price elasticity of -1.1. Escañuela Romana et al. (2023) apply a Quasi-Experimental Method (QEM) and obtain price elasticities of -0.7 for a dataset on U.S. domestic routes. Figure 1 summarizes the estimates of price elasticities in the literature review, comparing all relevant studies as given in Molloy et al. (2012) and additionally including more recent studies since 2000. The average elasticity estimates are -1.05, and -0.88 for the more recent studies.

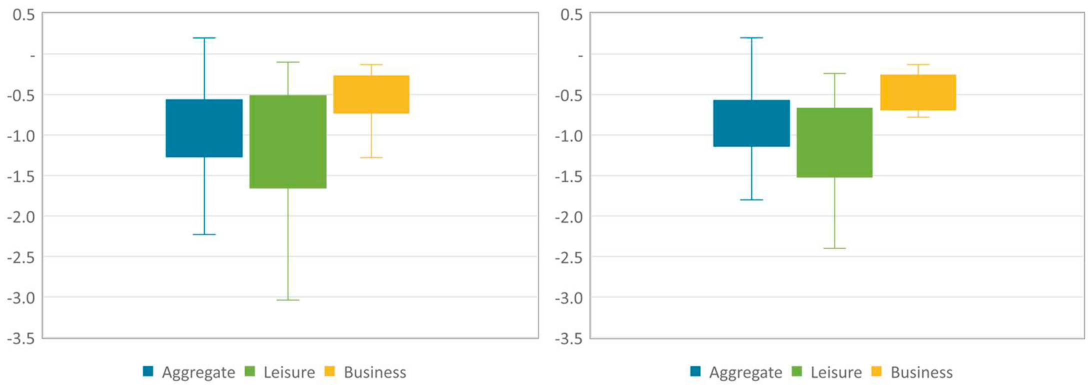

Fig. 1. Distribution of elasticity values from literature review for all studies (left hand side) and studies from 2000 (right hand side).

The empirical research on price elasticities of demand for air transport is diverse with regards to the geographical and time scope, and the papers that have been published also vary in their empirical strategy. One empirical issue that some papers address is the question of the endogeneity of airfares. Endogeneity arises when an explanatory variable is correlated with the error term. This violates the assumption necessary for estimator consistency, as the conditional expectation of the error term given the endogenous explanatory variable is non-zero (Baltagi, 2013). Due to reverse causality, prices impact demand, while demand, in turn, influences prices as a result of revenue management decisions. Molloy et al. (2012) for example address concerns regarding endogeneity using panel data and include airline-specific fixed effects in the model. InterVistas (2007), Granados et al. (2012a), Mumbower et al. (2014) and Morlotti et al. (2017) address endogeneity related to the price variable by employing a 2SLS instrumental variables (IV) approach alongside standard OLS. Average airfares in comparable markets (defined by similar distance) and competition variables are used as instruments (Mumbower et al., 2014; Molloy et al., 2012), along with route length, fuel prices and hub status (Granados et al., 2012a; InterVistas, 2007). While the elasticities derived by Morlotti et al. (2017) using different estimators demonstrate consistent results, significant differences are observed in the elasticity estimates from Granados et al. (2012a) and Mumbower et al. (2014) between the OLS and 2SLS methods. Specifically, OLS yields inelastic estimates (>-1), whereas the 2SLS method reveals elastic price elasticity estimates (<-1), consistent with the assumption that failure to control for endogeneity leads to underestimation of price elasticities (Mumbower et al. 2014).

3. Methodology and empirical model

The formal estimation of price elasticities of demand for air transport at the origin-destination level is typically conducted using an empirical air transport demand model or a gravity model. In these models, the number of air passenger flows between entities "i" and "j" is used as the dependent variable. Explanatory variables commonly include factors such as population, gross domestic product (GDP) per capita or total GDP, distance, airfares, and indicators representing specific relationships between the two entities. These bilateral indicators may capture historical ties, such as colonial relationships and shared languages, as well as economic arrangements like common currency systems, regional trade agreements, or open skies agreements (Boonekamp et al., 2018; Cristea et al., 2015; Gelhausen et al., 2020; Oesingmann, 2022a, 2022b; Piermartini and Rousová, 2013).

To derive current estimates of price elasticities in aviation, this study employs various empirical estimation techniques and conducts robustness checks. The methodology builds on established standards in gravity modeling, incorporating origin-year, destination-year, and city or country-pair fixed effects (Yotov et al. 2016). Issues of endogeneity will be addressed through the use of panel data, the inclusion of pair fixed effects, and the application of an instrumental variable (IV) approach. We use data at the country-pair and city-pair level and begin with the traditional gravity model approach to enable comparison with previous research findings. We therefore incorporate several control variables commonly used to explain passenger flows between two countries. In the next step, these control variables are replaced with the aforementioned set of fixed effects, leading to the structural version of a gravity model.

Equation (1) presents our initial linear specification at the country–country level, following the traditional gravity model framework. The variable X_{ijt} represents the number of air passengers on an origin–destination level between country i and country j at time t, with time t ranging from the year 2010 to 2019. β' indicates the vector of coefficients for the control variables and Y_{ijt} encompasses a set of common control variables utilized in gravity modelling. These include the unilateral variables gross domestic product (GDP) per capita ($gdp\_c\_o_{it}$ and $gpd\_c\_d_{jt}$) and population size (pop_o_{it} and pop_d_{jt}) and bilateral variables such as distance ($dist_{ij}$), common language ($comlang_{ij}$), colonial ties (col_{jt}) and border ($contig_{ij}$). The latter indicates if both countries share a common border. To capture the impact of business related and tourism related air travel, we insert a variable $trade_{ijt}$ giving the amount of trade flows between two countries and the variable $temp_{ijt}$. The variable $temp_{ijt}$ represents the differences in average annual temperatures between two countries, as introduced in an aviation gravity model by Cristea et al. (2015). However, it can only serve as a proxy for tourism-related travel since some country pairs may exhibit large temperature differences but still have low tourism flows due to other factors. Also, we insert a dummy variable *eia* for economic integration agreements (EIA) that facilitate free trade and a deeper economic integration between the participating countries.

$$X_{ijt} = \gamma fare_{ijt} + \beta' Y_{ijt} + \varepsilon_{ijt} \tag{1}$$

The variables *gdp, pop*, *trade* and *eia* are time-varying variables, while the remaining control variables are time-invariant variables. Our variable of interest $fare_{ijt}$ gives the average (base) airfare on a yearly basis of direct connections between country or city i and j at time t. The coefficient value of γ will provide the desired price elasticities. Finally, ε_{ijt} denotes the error term. In all our regressions, we use robust standard errors, clustered either by country or city-pair, to account for heteroscedasticity that impacts standard error estimates. All independent variables, except for the dummy variables, are transformed using their natural logarithms to allow the coefficients to be interpreted as elasticities. For the variable $temp_{ijt}$ we use the square root transformation due to zero values.

Second, in addition to using a linear estimator, we employ the Poisson Pseudo-Maximum Likelihood (PPML) estimator, a widely used method for estimating gravity models (Yotov et al., 2016). This approach enables us to examine whether significant differences emerge compared to results obtained with Ordinary Least Squares (OLS) estimates. Third, to address potential endogeneity concerns of the airfare variable, we apply an instrumental variable (IV) approach using a Two-Stage Least Squares (2SLS) linear estimator. We performed tests for endogeneity of the airfare variable and both the null hypothesis of the Durbin and Wu–Hausman tests, that the variable under consideration can be treated as exogenous, are rejected. In accordance with standard practices in the related literature, we use a Hausman-type price instrument, specifically the average base fare in other markets with similar route distances, as the primary instrumental variable for airfares (Molloy et al., 2012; Mumbower et al., 2014).

In the next step, we estimate the model using the full set of recommended fixed effects, resulting in the structural version of the gravity model in equation (2). Most of the variables in the vector Y are replaced by the three fixed effects ν_{ij}, λ_{it} and μ_{jt}. In addition, these fixed effects account for unobservable factors influencing our dependent variable. The remaining control variables besides airfares are bilateral trade and the EIA dummy variable.

$$X_{ijt} = \gamma fare_{ijt} + \beta' Y_{ijt} + \nu_{ij} + \lambda_{it} + \mu_{jt} + \varepsilon_{ijt} \tag{2}$$

To gain further insights and refine our empirical analysis, we also estimate our regression equations using data at the city-to-city level. This approach allows us to more accurately estimate elasticities for distance bins, such as short-haul or medium haul routes. To estimate regressions using OLS, PPML, and 2SLS, we utilize the STATA commands reghdfe, ppmlhdfe, and ivreghdfe, which enable the efficient computation of gravity models with a comprehensive set of fixed effects (Correia, 2023; Correia et al., 2020) . However, a corresponding command to apply a PPML estimator within an IV framework that incorporates multiple fixed effects is currently unavailable. Such a tool would be essential for accurately estimating structural gravity models in the presence of heteroscedasticity (Santos Silva and Tenreyro, 2006) and endogeneity.

4. Data

Our analysis relies on two primary data sources. Worldwide aviation-specific data, including annual passenger numbers, fare levels and distances are sourced from Sabre Market Intelligence (Sabre MI) on a yearly country-to-country and city-to-city basis (Sabre 2024). The Sabre MI database provides yearly passenger data starting from 2010. To exclude the impact of the COVID-19 pandemic, we restrict the dataset to the period from 2010 to 2019. The airfare levels in our dataset refer to base fare levels as defined by Sabre MI, representing the average yearly fare on an origin-destination basis, excluding taxes, and expressed in current US dollars. We define distance bins of 100 km to calculate our instrumental variable, the average fare in similar markets.

Standard variables for the gravity model, such as GDP per capita and population size at the country level and indicators of shared language, borders, and historical ties and bilateral trade amounts, come from CEPII's Gravity Model dataset (Conte et al., 2022). Data on whether countries are linked through an economic integration agreement are derived from Mario Larch's Regional Trade Agreements Database (Egger and Larch, 2008), while information on average temperatures is obtained from the World Bank's Climate Change Knowledge Portal (World Bank 2020). For the regressions based on country pairs, we use worldwide country data and direct flight connections. This results in over 3,700 country pairs, including domestic observations. Regressions on a city-pair basis focus on countries in geographic Europe, as defined by Sabre MI. This includes Western and Eastern European countries, as well as countries that are not part of the European Union, such as the United Kingdom and Turkey, for example. There are about 18,000 city pairs in the dataset, including intra-European and extra-European routes.

5. Results and discussion

5.1. Regressions at the country-level

Table 1 presents the results of our main regressions for worldwide data at the country-level using different estimators, namely OLS, PPML, and 2SLS. The first three columns in Table 1 display the regression results that include the full set of control variables but exclude any fixed effects. In contrast, the last three columns report the results from regressions incorporating the comprehensive set of fixed effects, which account for origin-year, destination-year, and pair-specific factors. For the instrumental variable (IV) approach, we utilize average fares in comparable markets, characterized by similar route distances, to instrument the airfare variable.

The control variables in our initial regressions generally exhibit the expected direction of impact on bilateral passenger flows. Specifically, GDP per capita, population size, distance, trade volumes, a shared language, and colonial ties all positively influence passenger flows between countries. Additionally, greater temperature differences are associated with an increase in (tourist) traveler numbers, although this effect is statistically significant only in the OLS estimates. Regarding our variable of interest, the estimated price elasticity is approximately -1.2 for both the OLS and PPML models without fixed effects. The results are consistent with recent estimates at the aggregate level that use gravity models without fixed effects (Gelhausen et al., 2020). The IV approach yields a notably greater price elasticity estimate of approximately -1.49. This result is also consistent with findings from previous research, which have similarly observed larger elasticities when comparing 2SLS estimates to those obtained using OLS (Mumbower et al., 2014; InterVistas, 2007; Granados et al., 2012a).

Columns three to six in Table 1 present the regression results obtained after including the full set of fixed effects. Notably, the inclusion of these fixed effects significantly reduces the magnitude of the price elasticity across all models. Specifically, the elasticity decreases to approximately -0.6 for the OLS estimates, to less than -0.4 for the PPML model, and slightly below -0.9 for the IV approach. Controlling for origin-year, destination-year, and pair-specific fixed effects captures unobserved heterogeneity, which likely influences the relationship between fares and passenger flows. As a result, the fixed effects models should provide a more nuanced and potentially more accurate estimation of price sensitivity. Hence with regards to the relatively low levels of price elasticities obtained with OLS and especially PPML, endogeneity matters are likely to bias coefficient estimates. The Hausman test for endogeneity reveals that differences in coefficients are systematic, so that OLS gives biased estimates due to the endogeneity of airfares. Diagnostic tests, including the Durbin–Wu–Hausman and Kleibergen–Paap statistics, confirm valid instruments and model consistency, with robust clustered errors and low multicollinearity supporting the regression assumptions.

Table 1. Main regression results for worldwide data (country-country level)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	PPML	2SLS	OLS	PPML	2SLS
VARIABLES	lnpax	pax	lnpax	lnpax	pax	lnpax
lnfare	-1.183***	-1.207***	-1.485***	-0.629***	-0.367***	-0.870**
	(0.031)	(0.064)	(0.103)	(0.022)	(0.028)	(0.344)
lngdp_c	0.399***	0.436***	0.405***			
	(0.013)	(0.039)	(0.013)			
lnpop	0.408***	0.437***	0.411***			
	(0.012)	(0.047)	(0.013)			
lndist	0.255***	0.085	0.440***			
	(0.036)	(0.094)	(0.077)			
lntrade	0.104***	0.143***	0.104***	0.010***	0.034***	0.011***
	(0.005)	(0.026)	(0.005)	(0.003)	(0.006)	(0.003)
sqtemp	0.022*	0.030	0.020			
	(0.013)	(0.025)	(0.013)			
comcol	0.344***	0.340***	0.335***			
	(0.053)	(0.114)	(0.053)			
comlang	0.962***	0.646***	1.015***			
	(0.037)	(0.074)	(0.040)			
border	-0.227***	-0.486***	-0.166**			
	(0.063)	(0.111)	(0.065)			
eia	0.057	-0.059	-0.003	0.309**	0.447***	0.328***
	(0.045)	(0.114)	(0.047)	(0.121)	(0.149)	(0.118)
Observations	37,768	37,768	37,768	41,028	41,028	41,028
R^2/pseudo R^2	0.701	0.763	-	0.983	0.994	-
Country pair FE	NO	NO	NO	YES	YES	YES
Destination/Origin & Year FE	NO	NO	NO	YES	YES	YES
Sample	Worldwide	Worldwide	Worldwide	Worldwide	Worldwide	Worldwide

Notes: (Robust) standard errors, clustered by country-pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. The price variable is instrumented with the average fare variable in similar markets in 2SLS regressions. Instrument test statistics for 2SLS estimates in regressions (3) and (6): Kleibergen-Paap rk Wald F statistic = 1,338.74 and 3.88.

Interestingly, while OLS and PPML produced similar results when estimating the model without fixed effects, their estimates diverge by 0.26 in the models that include fixed effects. The remaining control variables, including the volume of bilateral trade flows and the existence of an economic integration agreement, are both highly significant and positively influence passenger numbers. Compared to the regressions without fixed effects, the EIA variable now shows the expected direction of impact. The test statistics suggest fare in similar markets is a weak instrument in the fixed-effects regression (column 6), as the Kleibergen-Paap rk Wald F statistic falls below the threshold of 10. Hence, this issue does not arise in the regression without fixed effects (column 3), where the F statistic is clearly above the critical threshold (1,338.74). Therefore, we do not generally consider our instrumental variable as weak.

5.2. Regressions at the city-level

We extend our analysis to the city-pair level to calculate Europe specific and distance-related price elasticities. As highlighted in existing literature, price elasticity varies by region and travel distance, with different routes likely exhibiting distinct elasticity values. Table 2 presents city-to-city regressions for all routes connecting Europe to the rest of the world at a global scale. Compared to the findings of the price elasticities at the country-level, price elasticities for Europe based travel are higher with an aggregate elasticity of -1.27. Previous research also showed higher elasticity levels for air travel originating in Europe (InterVistas, 2007). OLS and PPML exhibit much lower elasticities due to not controlling for endogeneity, as experienced in the regressions at the country level.

Table 2. Main regression results for Europe-worldwide data (city-city level)

	(1)	(2)	(3)
	OLS	PPML	2SLS
VARIABLES	lnpax	pax	lnpax
lnfare	-0.809***	-0.395***	-1.271***
	(0.032)	(0.020)	(0.096)
Observations	186,606	186,606	186,606
City pair FE	YES	YES	YES
Destination/Origin & Year FE	YES	YES	YES
Sample	Europe-Worldwide	Europe-Worldwide	Europe-Worldwide

Notes: (Robust) standard errors, clustered by city-pair, are given in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. The price variable is instrumented with the average fare variable in similar markets in 2SLS regressions. Instrument test statistics for 2SLS estimates in regression (3): Kleibergen-Paap rk Wald F statistic = 182.35.

Table 3 presents the regression results for three subsets of the city-pair dataset, categorized by distance: less than 1,000 km, between 1,000 and 3,000 km, and over 3,000 km. Regressions are performed using both OLS and 2SLS. In all the 2SLS regressions at the city-pair level, the Kleibergen-Paap rk Wald F statistic is higher than the critical value of 10, implying that our instrument variable is a valid instrument (not weak). The highest price elasticities are observed in the medium-haul range, with estimates of -1.0 for OLS and -1.5 for 2SLS. For OLS, the lowest elasticity is associated with long-haul distances (-0.788), while for 2SLS, short-haul routes exhibit a lower elasticity compared to the other distance ranges (-1.22). It can be observed that elasticity estimates vary significantly depending on the estimator used, a pattern also witnessed in previous research. OLS generally produces lower estimates compared to the IV approach. Interestingly, with the 2SLS estimates, the general assumption that long-haul routes exhibit lower elasticities than short-haul routes is challenged by our current estimates, noting that underlying studies did not correct for endogeneity of airfares (Brons et al., 2002; Gillen et al., 2007; InterVistas, 2007). Given that endogeneity of airfares is inherent, OLS estimates are likely biased, making the 2SLS model with fixed effects the preferred method for obtaining reliable estimates. The Hausman test supports the assumption that OLS estimates are biased upwards, as with the city-level dataset also, the null hypothesis needs to be rejected that differences between OLS and 2SLS are not systematic. Our elasticity estimates are broadly consistent with international studies (Brons et al., 2002; Gillen et al., 2007; Gelhausen et al., 2020) but somewhat more elastic than comparable European findings in recent literature.

Table 3. Additional regressions results for Europe-worldwide and different distances (city-city level)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS lnpax	OLS lnpax	OLS lnpax	2SLS lnpax	2SLS lnpax	2SLS lnpax
lnfare	-0.834***	-1.011***	-0.788***	-1.220***	-1.536***	-1.417***
	(0.098)	(0.078)	(0.041)	(0.137)	(0.141)	(0.232)
Observations	36,097	52,466	91,881	36,097	52,466	91,881
Country pair FE	YES	YES	YES	YES	YES	YES
Destination/Origin & Year FE	YES	YES	YES	YES	YES	YES
Sample	Europe-Worldwide <1,000km	Europe-Worldwide 1,000-3,000km	Europe-Worldwide >3,000km	Europe-Worldwide <1,000km	Europe-Worldwide 1,000-3,000km	Europe-Worldwide >3,000km
R^2	0.872	0.831	0.902	-	-	-
Kleibergen-Paap rk Wald F statistic	-	-	-	107.91	24.44	368.66

Notes: (Robust) standard errors, clustered by city-pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. In the 2SLS regressions, the airfare variable is instrumented with the average fare in similar markets.

5.3. Practical Implications

The empirical results presented above provide several practical insights into how fare changes may influence passenger demand across different markets and route types. The estimated global elasticity of –0.87 indicates that air travel demand is moderately inelastic overall, while the higher sensitivities observed for European-origin (–1.27) and medium-haul routes (–1.5 in 2SLS estimates) suggest substantial variation in price responsiveness. These findings imply that fare adjustments arising from external cost factors such as carbon pricing or taxation may have differentiated effects on passenger volumes across regions. In particular, routes with higher elasticities are more likely to experience notable demand declines in response to price increases.

Incorporating these insights on differentiated elasticity estimates into policy and forecasting models can enhance the accuracy of simulations related to regulatory interventions in aviation. Recognizing the heterogeneity of demand responses across regions and distances allows policymakers and analysts to better assess the behavioral and environmental implications of pricing-based measures, ensuring that such instruments are designed with realistic expectations of how passengers respond to changing airfares.

6. Conclusion

This study provides updated estimates of price elasticities in the aviation sector, utilizing a comprehensive dataset at the global scale sourced from Sabre Market Intelligence (MI). This dataset, encompassing detailed demand and price information at both the country and city level, spans a 10-year period from 2010 to 2019. Apart from integrating modern gravity modelling standards like including a specific set of fixed effects, the study addresses the critical issue of endogeneity through the application of a Two-Stage Least Squares (2SLS) approach. A key finding is the significant variability in current estimates of price elasticity, influenced by the choice of estimator, the inclusion of fixed effects, and therefore the method employed to handle endogeneity. These factors make it challenging to pinpoint a singular, definitive estimate for the price elasticity of demand in aviation. Our study is in line with previous research that shows more inelastic results when estimating price elasticities using OLS and more elastic estimates when using an IV approach. Our analysis suggests a global price elasticity estimate of -0.87. Notably, demand for travel originating in Europe exhibits greater price sensitivity, with an elasticity of -1.27. Moreover, medium-haul routes show greater price elasticity than short-haul or long-haul routes.

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