Meta-analysis of the Ticket Price Elasticity for Air Travel Demand

Katerina, Kattavenaki[1], Ioanna, Pagoni[1,2], George, Yannis[1]

[1]National Technical University of Athens
[2]University of the Aegean

Email:

Katerina Kattavenaki
katerina.kattavenaki@gmail.com

Ioanna Pagoni
ipagoni@aegean.gr

George Yannis
geyannis@central.ntua.gr

Abstract

This paper aims to systematically review the literature related to the estimation of air ticket price elasticity and conduct a meta-analysis to examine the effect of various determinants of ticket price elasticity estimates. A total of 258 estimates of air ticket price elasticity of demand were collected from 44 international studies from 1974 to 2020. Meta-regression models were developed, including fixed-effects and random-effects models. The independent variables of the meta-regression are related to various geo-economic (coverage area, flight distance, passenger category, etc.) and study-descriptive characteristics (data time period, publication type, etc.) of each individual sample estimate of the reviewed studies. The results indicate the significance of several determinants such as fare class, flight distance, the study's publication type and the demand model's characteristics on the estimated ticket price elasticities.

Keywords: *air-travel demand, price elasticity of demand, airline ticket price, meta-analysis, systematic review, PRISMA.*

Σύνοψη

Στόχος της παρούσας έρευνας είναι η διερεύνηση των καθοριστικών παραγόντων στους οποίους αποδίδεται η μεταβλητότητα στις παρατηρήσεις της βιβλιογραφίας στην ελαστικότητα ζήτησης ως προς την τιμή του αεροπορικού εισιτηρίου (ticket price elasticity of demand), αξιοποιώντας τις τεχνικές της συστηματικής ανασκόπησης και μετα-ανάλυσης. Συγκεντρώθηκαν συνολικά 258 παρατηρήσεις της ελαστικότητας της ζήτησης του αεροπορικού εισιτηρίου από 44 μελέτες που έχουν διεξαχθεί διεθνώς από το 1974 έως το 2020. Συνθέτοντας τα ευρήματα των μελετών αυτών, αναπτύχθηκαν μοντέλα μετα-παλινδρόμησης και συγκεκριμένα ένα μοντέλο σταθερών (fixed-effects model) και ένα τυχαίων επιδράσεων (random-effects model), με σύγκριση των οποίων καθορίστηκε το βέλτιστο ερμηνευτικό μοντέλο. Οι ανεξάρτητες μεταβλητές του μοντέλου, σχετίζονται με διάφορα γεω-οικονομικά (απόσταση πτήσεως, κατηγορία επιβατών, περιοχή κάλυψης κ.α.) και περιγραφικά χαρακτηριστικά (έτος δημοσίευσης, είδος δημοσίευσης, μεθοδολογία κ.α.) κάθε επιμέρους εκτίμησης των μελετών του δείγματος. Από τα αποτελέσματα της έρευνας εξετάστηκε η σημασία διαφόρων καθοριστικών παραγόντων, όπως η κατηγορία ναύλου, η απόσταση πτήσεως, ο τύπος δημοσίευσης μιας μελέτης και τα χαρακτηριστικά του μοντέλου ζήτησης.

Λέξεις κλειδιά: *αεροπορική ζήτηση, ελαστικότητα ζήτησης ως προς την τιμή, τιμή του αεροπορικού εισιτηρίου, μετα-ανάλυση, συστηματική ανασκόπηση.*

1. Introduction

In the last few decades, air transport has undergone drastic changes. Growing demand, airport privatization, the creation of airline alliances and new technological developments are trends that have shaped the aviation industry as we know it today. Passenger traffic in the European Union surpassed 1 billion in 2019, marking a 47% increase since 2008 (Eurostat, 2020). However, with the COVID-19 spike in 2020, air passengers dropped by 73%, causing a major blow to the industry. Similar fluctuations in passenger traffic have been observed in the past, due to terrorist attacks (9/11), pandemic outbreaks (H1N1 flu) and major sporting events (World Cup, Olympic Games, etc.).

Against this background, considerable interest has been observed in forecasting demand and identifying the factors that influence it. This is also evident from the extensive number of studies carried out on this topic. Specifically, of particular interest is the extent to which the ticket price affects demand, as expressed by the ticket price elasticity of air-travel demand. This metric is very useful for several aviation stakeholders and the civil aviation authorities, which have the task of regulating economic activity in air transport to the airlines.

However, as reported by Brons et al. (2002), the calculation of the price elasticity of demand presents difficulties as information on passenger traffic and ticket prices is often not easily accessible. Alternatively, it is possible to carry out the research using the meta-analysis procedure, by synthesizing the findings of several existing studies by different researchers. Looking at the results of the literature, there seems to be a large variability in the estimates. The aim of this study is to investigate the determinants to which this variability is attributed, utilizing the techniques of systematic review and meta-analysis.

The first meta-analysis conducted on the price elasticity of air-travel demand was by Brons et al. (2002). In their study, 37 studies from 1974 to 2000 were analysed and a total of 204 elasticity values were collected, with a mean value of -1.146. The explanatory variables of the model were Gross Domestic Product (GDP), the year of data collection, flight distance, time horizon, study location, method of analysis and fare category. The results of the study showed that, in the long-run, consumers seem to be more sensitive to the air ticket price. Also, as expected, business-class passengers are less sensitive to price changes than economy-class ones. It was also very interesting to note that according to the results, European passengers, despite having more substitutes (train, bus) than American and Australian passengers, are not more sensitive to the price of an airline ticket.

Later on, Kucherenko and Dybvik (2019) collected a total of 443 observations from 68 surveys covering the period from 1946 to 2016. In this study, a model for economy-class passengers only (leisure model) and a model for business and economy-class passengers together (aggregated model) were created. The mean value of the estimated elasticity was -1.081 and -0.789 for each model respectively. The meta-regression models were generated using the Ordinary Least Squares (OLS) method. Fare class, study location, time horizon, data collection year and estimation method proved to be the most critical variables.

The above discussion indicates that mean price elasticities differ considerably between these two meta-analysis studies. In the study of Brons et al. (2002), air travel demand is elastic (mean $|e|>1$) to the ticket price, while in the 2019 study, it is inelastic (mean $|e|<1$ for the aggregated model). This might be attributed to the changing environment of the aviation industry in terms of prices between the study periods. In addition, it should be noted that the recent study of Kucherenko and Dybvik (2019) applied the OLS method which is not suitable for the panel meta-analysis data. Considering the above, there is a need for further research, that includes the most recent data of air travel price elasticities and applies a method that overcomes the restrictions of the OLS method.

2. Our approach

2.1 Systematic review

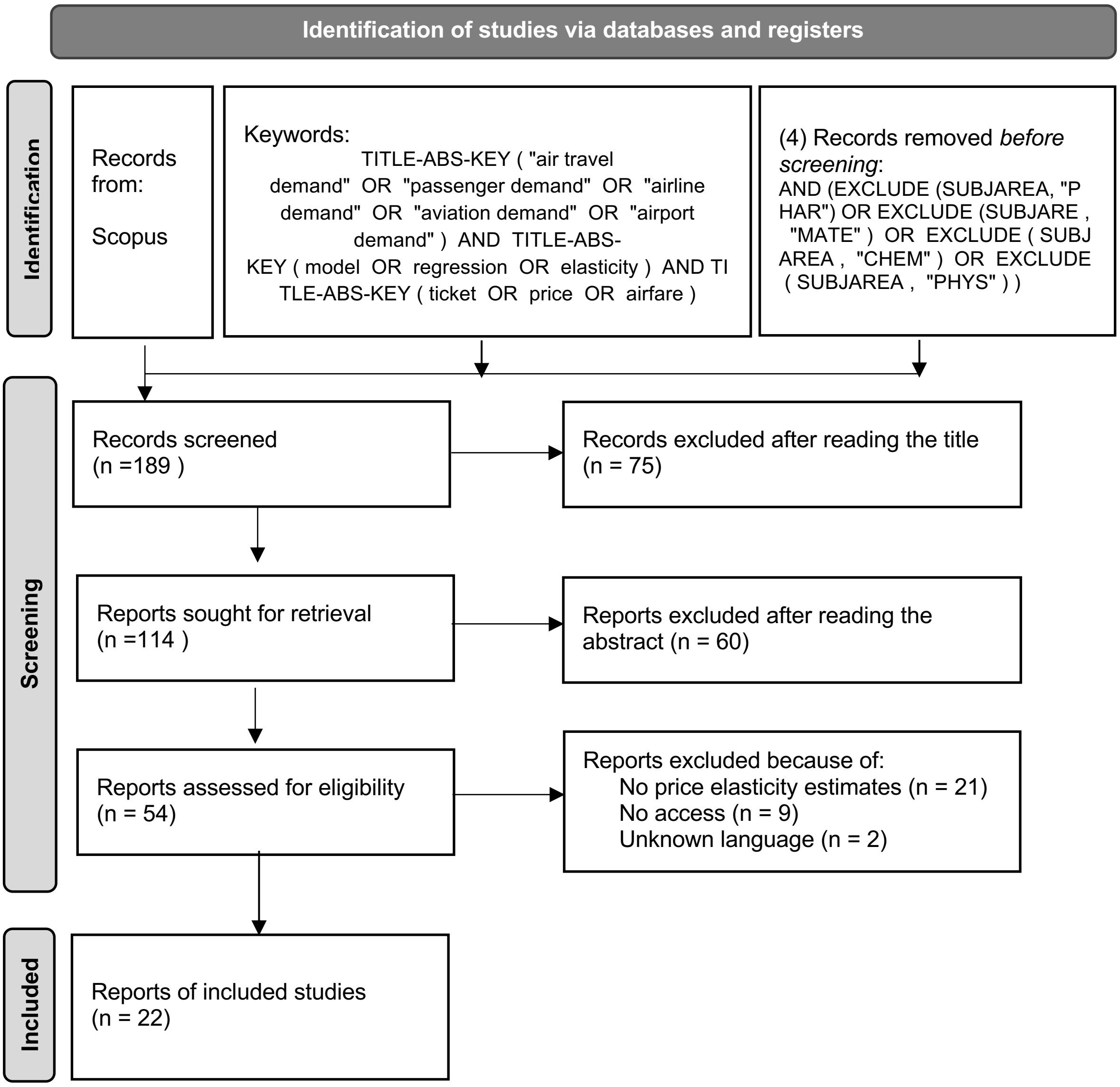
Systematic review and meta-analysis are the first and second step, respectively, of a process of combining the results of several studies regarding a specific scientific question, in order to calculate with greater precision and validity an aggregate result, which essentially assesses the relationship between the determinants and the outcome (Galanis, 2009).

The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement is the best-known protocol for conducting a systematic review, which suggests a standardized way to ensure a clear and comprehensive review process. The main purpose of PRISMA is to assist authors in improving systematic reviews and meta-analyses. It also enables the evaluation of the methods used in research and therefore contributes to the reliability of its findings (Page et al., 2021).

The subject of this study is essentially a comparative process of re-evaluation of the price elasticities for air-travel demand, which have been calculated in previous studies. The set of observations was drawn from existing studies in the literature where researchers have calculated one or more values of air-ticket price elasticity. The search for appropriate studies was conducted using the systematic review process and following the protocol of the PRISMA methodology.

The Scopus search engine was used to conduct this systematic review, using the advanced search tool. After the appropriate keywords were selected, the following search query was used: *"TITLE-ABS-KEY ("air travel demand" OR "passenger demand" OR "airline demand" OR "aviation demand" OR "airport demand") AND TITLE-ABS-KEY ("model" OR "regression" OR "elasticity") AND TITLE-ABS-KEY ("ticket" OR "price" OR "airfare")"*. The whole process of the systematic review is explained in detail in the following PRISMA flow diagram (Figure 1).

The above query led to 192 studies, 4 of which were easily excluded before screening since they belonged to subject areas unrelated to our research. The remaining 189 studies were thoroughly reviewed, in order to collect studies that contain at least one estimate of price elasticity and sufficient information on how the researcher arrived at the particular result. To separate them from irrelevant research or research with incomplete data, the review process was conducted in three steps. First, 75 studies were excluded after reading their title, then 60 more were excluded after reading their abstract and finally, 32 were excluded because 21 of them didn't contain price elasticity estimates, 2 of them were in an unknown language and 9 of them we did not have access to. In an effort to enrich the sample of observations, 22 studies from the references in the existing meta-analyses on the topic (Brons et al., 2002; Kucherenko and Dybvik, 2019) were also added. In the end, 44 surveys from 1974 to 2020, with a total of 258 observations of air-ticket price elasticity of demand were collected, which will be the dependent variable of the meta-regression models.



Adapted from: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71
For more information, visit: http://www.prisma-statement.org/

Figure 1: *PRISMA 2020 flow diagram for systematic review*

2.2. Meta-analysis and meta-regression analysis

The second step, meta-analysis, consists of a descriptive statistical analysis of the data obtained from the systematic review and further analysis that may be conducted with the support of the meta-regression models.

The meta-analysis data are usually panel data, corresponding to a sample of N units (countries, regions, households, etc.) who are each observed in one of T time periods (years, quarters, months, etc.). In the case of meta-analysis, the researcher collects data from different studies (units), but within a single study, different observations of the effect size (ticket price elasticity for air-travel demand) may be recorded. Because these observations belong to the same study, they may have some common characteristics (method of analysis, etc.), leading to their potential correlation. As a result, since one of the fundamental assumptions of the ordinary least squares (OLS) method is violated, panel data models are usually employed for the meta-regression analysis such as fixed-effects and random-effects models. The general form for the panel data models (e.g. fixed-effects or random-effects models), is as follows:

$$y_{it}= \beta x_{it} + c_i + \varepsilon_{it} \qquad \textbf{(1)}$$

where y_{it} is the dependent variable, that is a linear function of the independent variables (x_{it}) and an individual specific unobservable factors c_i. The terms fixed and random effects, refer to the assumptions related to the individual-specific constant terms c_i. If there is a dependence between these unobserved factors and the observed independent variables, we employ the fixed effects approach. If, on the other hand, these effects are independent of the observed independent variables, we use the random effects estimator.

Heterogeneity between studies and publication bias are two methodological issues that may arise when conducting a meta-analysis and may reduce the reliability and the validity of the results. Therefore, this paper has analysed the results in order to identify the existence and address these issues and make sure their data sample is credible to use in a meta-analysis (see Sections 3.4 and 3.5).

From each study, apart from the elasticity estimates, information related to its geographic, economic, demographic as well as other descriptive characteristics were recorded in the database and will later form the explanatory variables of the model. After collecting as much information as possible, the final database was completed in an excel spreadsheet that consisted of 59 columns and 258 rows. As shown in Figure 2, the 55 created explanatory variables can be divided into variables that refer to the geo-economic or study-descriptive characteristics of each study in this meta-analysis.

Explanatory variables

Geo-economic characteristics:	Study-descriptive characteristics:
-Geographical location (N.America, Europe, Asia, Aus/NZ, Other) -Distance (short-haul, medium-haul, long-haul) -Fare class (Business, Economy, Aggregated) -Route (International, Domestic)	-Publication year -Average year of data collection period -Publication type (Conference, Journal, Working paper) -Time-horizon (short-term, long-term) -Data aggregation level (National, City-pair, airport-pair, MAS) -Explanatory variables (GDP, Income, Population, Frequency, Fare, Yield, Oil, Hub, Delay, LCC, Substitute mode) -Standard error reported -Demand data collection (Annual, Quarterly, Monthly, Daily) -Study type (aggregated, disaggregated) -Estimation method (FE, MLE, OLS, WLS, 2SLS, 2SGMM, LIML) -Demand form (Dynamic, Static) -Endogeneity treated -IV

Figure 2: *Explanatory variables used in the meta-analysis*

3. Meta-analysis Results

3.1 Descriptive Statistical Analysis

A descriptive statistical analysis was carried out before the development of the meta-regression models. Looking at certain descriptive statistics on the price elasticity estimates, we gathered useful insights about the relationship of different factors and air travel demand elasticity.

As shown in Table 1, the overall mean price elasticity for the total of 258 observations from the years 1974 to 2020, was estimated at -0.97. In a similar study by Brons et al. (2002), which collected surveys from 1974 to 2000, the mean price elasticity was -1.146. Comparing these values, it appears that the results of the more recent studies from 2000 to 2020 yielded an increase (value closer to 0) in elasticity of about 18%. Therefore, it appears that demand is less affected by changes in ticket price than twenty years ago.

Table 1: *Descriptive statistics for the price elasticity of demand*

Price elasticity of demand	
No. of observations	258
Mean	-0.97
Median	-0.87
Standard deviation	0.72
Min	-4.77
Max	0.47

Examining the effects of elasticity under different demand conditions provides important insights into its behavior. Furthermore, by creating appropriate graphs it is possible to visualize the variation of the results in the literature. As shown in Table 2, the majority of the observations in our sample came from studies related to the North American market, with 114 out of 258 observations. The European market follows closely with 52 observations and the Australian/New Zealand market with 50 observations. Fewer observations are related to the Asian market (16 observations), while the remainder (26 observations) relate to other regions of the world (Brazil, South Africa, etc.). Apart from being the most studied region in the literature, North America was also the first to be studied in 1974, while European studies were the next ones appearing a little later in 1977.

Table 2*: Descriptive statistics for the price elasticity of demand by Location*

Location	**Mean**	**St. deviation**	**No. of observations**
North America	-1.15	0.78	114
Europe	-0.81	0.58	52
Australia/New Zealand	-0.69	0.55	50
Asia	-0.81	0.8	16
Other	-1.12	0.71	26

The results for all geographical regions are gathered in a histogram, in which the differences in the distribution of observations per area can be seen. In Figure 3, Europe, Australia/New Zealand and Asia follow a similar pattern, with the majority of observations concentrated in the range between -0.3 and -0.1. For North America the largest number of observations is concentrated between -1.3 and -1.1. Similar differences are noted in the average elasticity values by location (Table 2). Europe and Asia are quite close with mean elasticity value of -0.808 and -0.813 respectively. For Australia/New Zealand demand seems to be even more inelastic with a mean value of -0.69. In contrast, demand for North America and the rest of the world ('Other') is elastic, with an average elasticity value of -1.148 and -1.125 respectively.

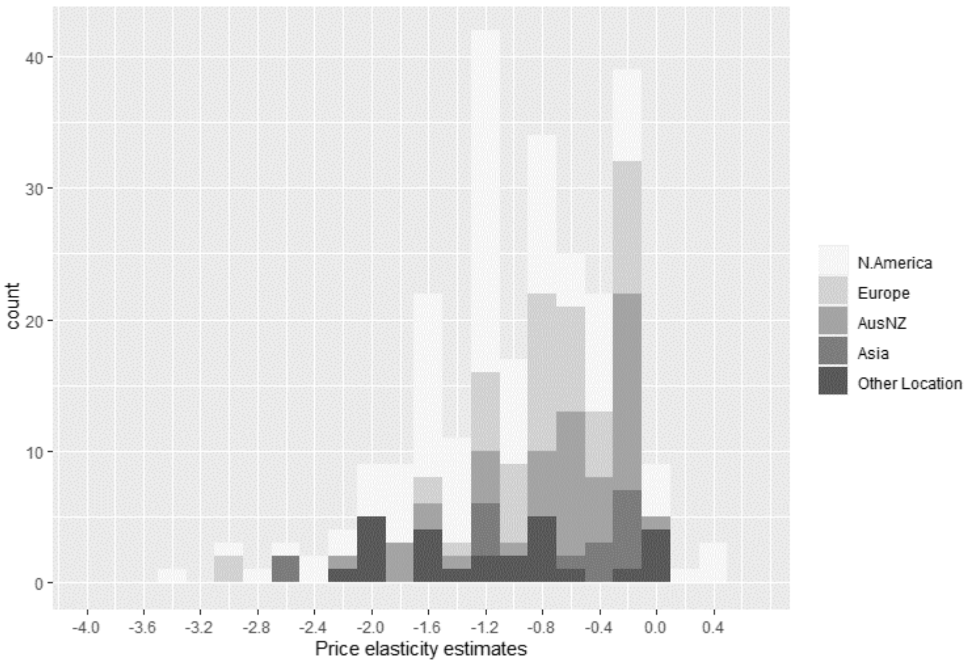
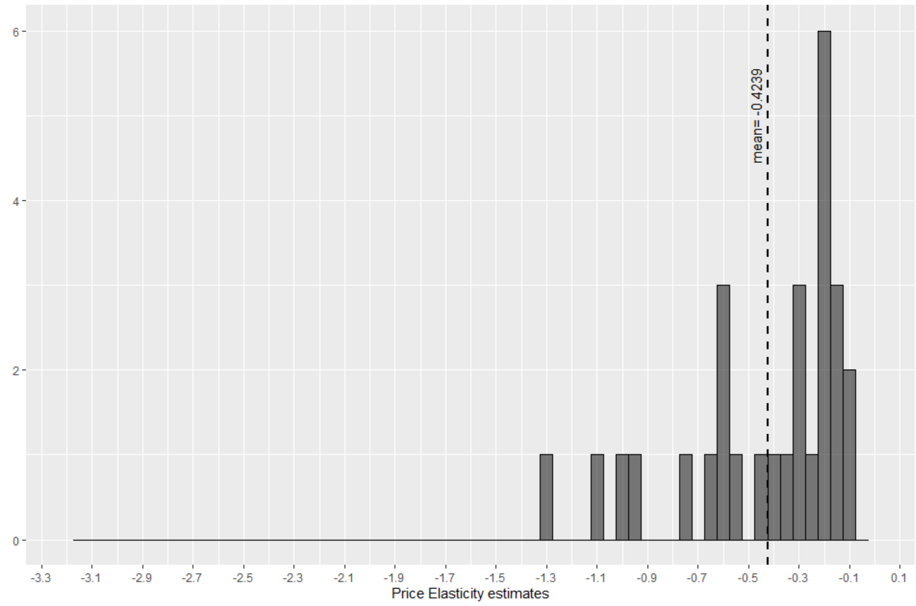
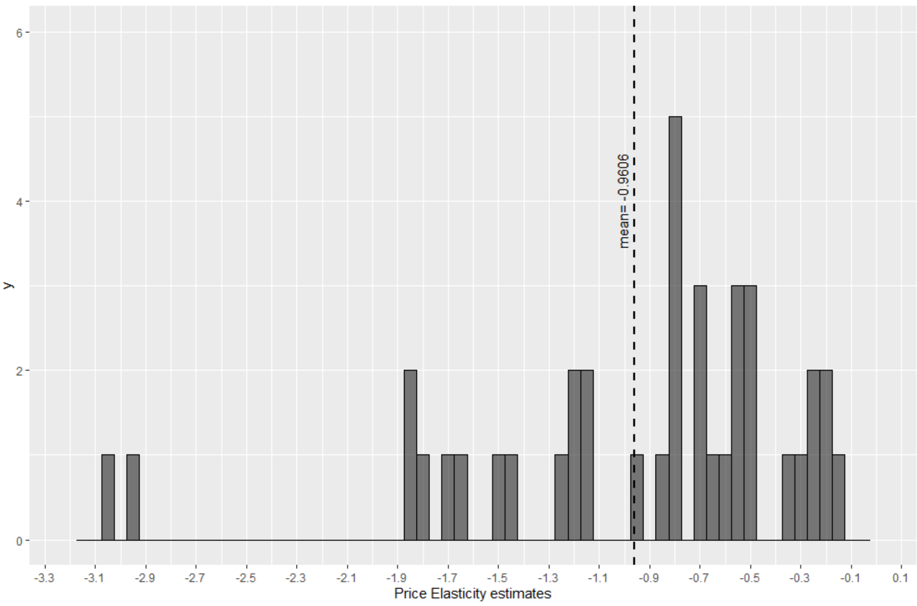


***Figure 3:** Distribution of price elasticity estimates by Geographical Location*

In the case of business class passengers only, the mean price elasticity of demand is -0.424, while for economy class passengers only, it's -0.961. This could be explained by the fact that business class passengers, usually travelling for business purposes, are less sensitive to the ticket price and more sensitive to the date and time of the flight, which does not give them many alternative options. They also do not pay for their travel themselves, but their expenses are covered by their employers. Leisure travellers on the other hand, are more sensitive to the price of the air ticket, as they aim to maximize the utility of air travel while limiting their movements around a certain budget. The difference in elasticity numbers between business and economy class passengers can also be seen by comparing Figures 4 (a) and (b). In conclusion, when it comes to leisure travel, consumers are more sensitive to the price of airfare than when it comes to business travel.



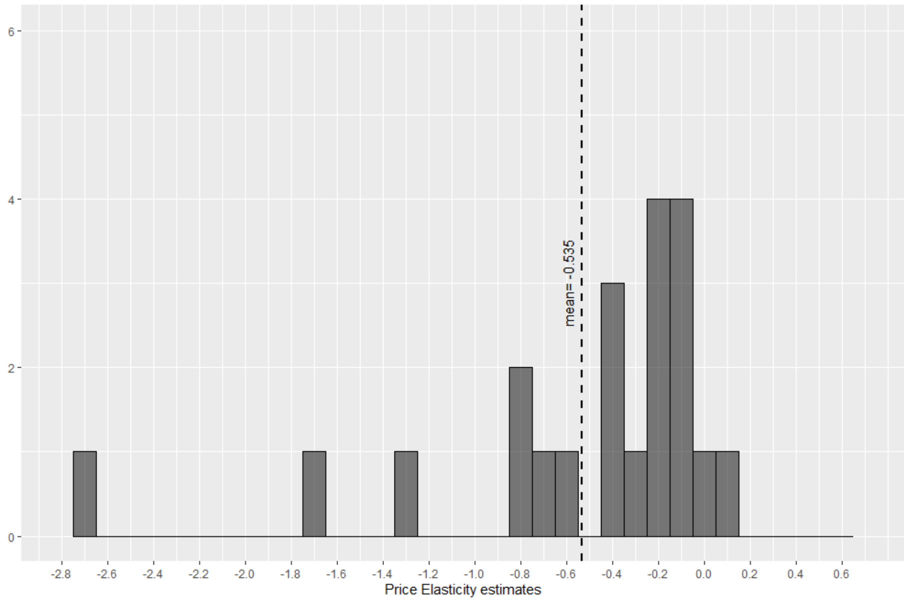
(a)



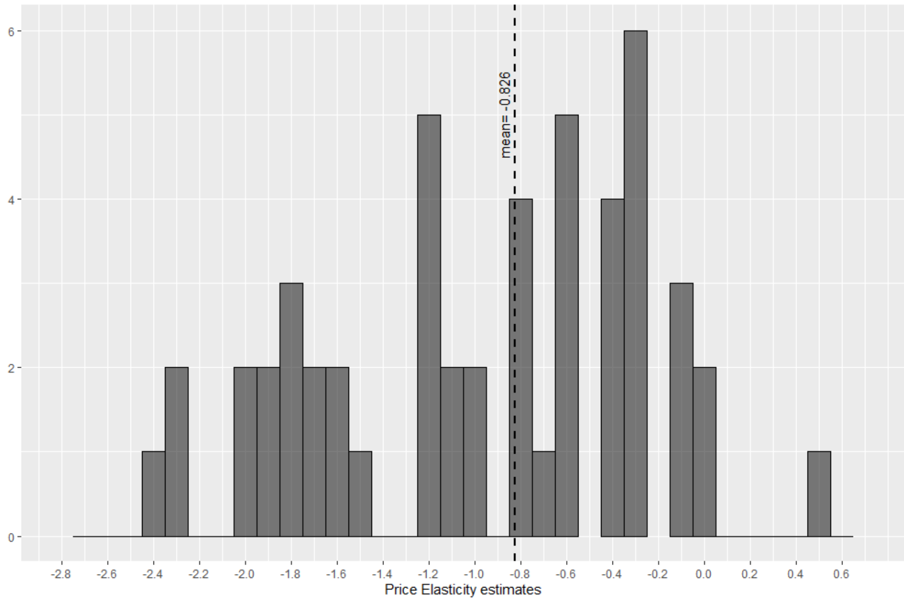
(b)

Figure 4: *Distribution of price elasticity estimates for (a) business class and (b) economy class passengers*

Similar differences are observed in the elasticity values depending on the time horizon defined by the researcher in his study. Long-term elasticity results do not only take into account the immediate economic impact of the change in ticket price but also take into account the market adjustments to new data and new demand trends. In the long run, consumers and companies are better adapted to price changes than in the short run. As shown in Figures 5 (a) and (b), in the long run, demand (-0.826) tends to be more elastic than in the short run (-0.535).



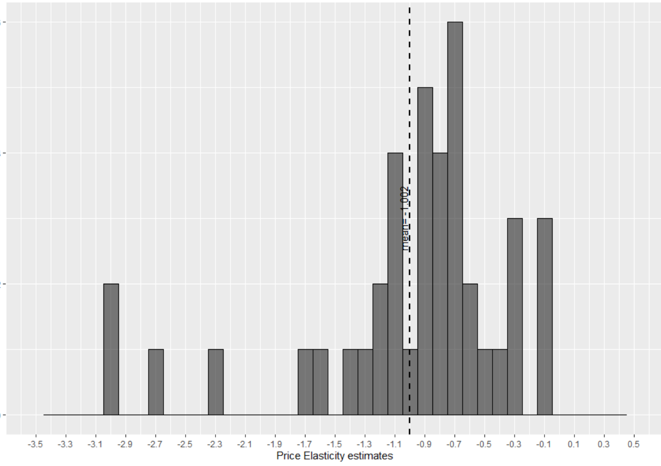
(a)



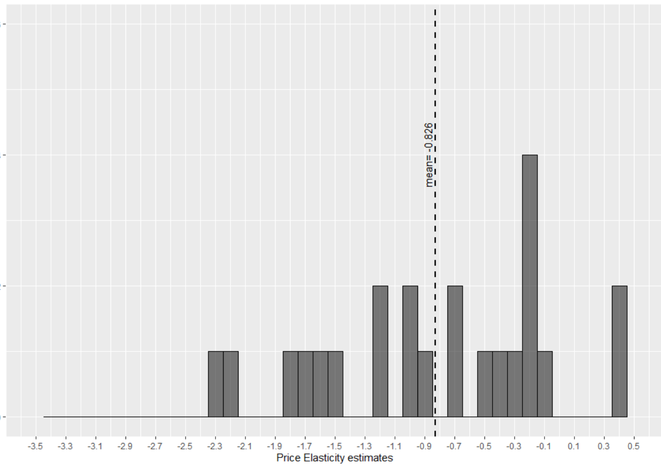
(b)

***Figure 5:** Distribution of (a) short-term price elasticity estimates and (b) long-term price elasticity estimates*

The mean elasticity values also vary according to the distance market. Figure 6 shows the distribution of observations for the three distance categories: short-haul (<500 miles), medium-haul (500-1500 miles) and long-haul (>1500 miles). Long-haul flights (-0.724) correspond to less negative elasticity values than short-haul flights (-1.002). In general, as the distance increases, the influence of the ticket price on demand decreases. This may be due to the lack of travel alternatives for longer-distance flights.



(a)



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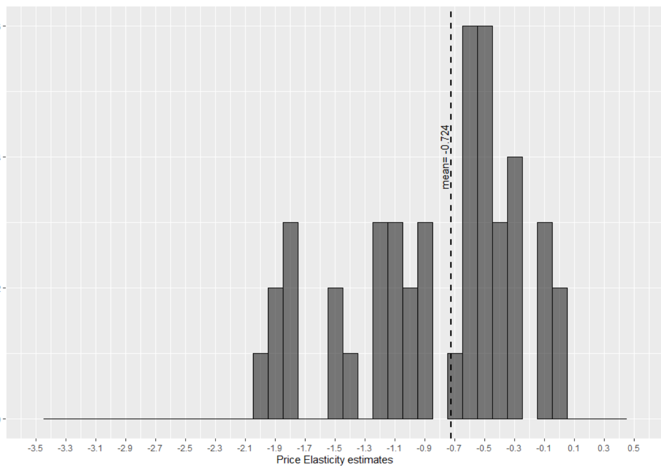

(c)

***Figure 6:** Distribution of price elasticity estimates for (a) short-haul flights (b) medium-haul flights and (c) long-haul flights*

3.2 Meta-regression analysis

To select the appropriate explanatory variables from the database to formulate a model with high explanatory power and reliable results, a significant number of tests were performed, starting with the Backward search method, where all the variables are initially entered into the model and then removed one by one sequentially. The explanatory variables should be well correlated with the dependent variable, but not highly correlated with each other. Following these criteria, the most critical explanatory variables included in the meta-regression models are presented in Table 3.

***Table 3:** Description of the explanatory variables used in the meta-regression models*

Variable	Type	Description
Dataset_Year	Continuous variable	Average year of data collection period
Conference	Dummy variable	=1 if study was published in a conference
North_America	Dummy variable	=1 if the study was conducted in North America
Short-haul	Dummy variable	=1 if elasticity refers to short-haul market (<500 miles)
Medium-haul	Dummy variable	=1 if elasticity refers to medium-haul market (500-1500 miles)
Long-haul	Dummy variable	=1 if elasticity refers to long-haul market (<1500 miles)
Short-term	Dummy variable	=1 if elasticity pertains to short-term
Economy	Dummy variable	=1 if elasticity refers to economy class passengers
Airport-pair	Dummy variable	=1 if data refers to airport-pair level
INC	Dummy variable	=1 if income is included in the demand model as an explanatory variable
Frequency	Dummy variable	=1 if flight frequency is included in the demand model as an explanatory variable
SE_reported	Dummy variable	=1 if standard error is reported in the study
Daily	Dummy variable	=1 if daily data were used to estimate demand
Linear	Dummy variable	=1 if the demand model is linear
IV	Dummy variable	=1 if Instrumental Variables (IV) were used for the demand model

For the statistical analysis of the data, an optimal meta-regression model was sought that describes the relative importance of various variables with the dependent variable of the model, the ticket price elasticity of air-travel demand. In particular, a fixed-effects model and a random-effects model were developed in R. The results of the meta-regression models, as well as several diagnostic tests that were run, are presented in Table 4.

Since both models satisfy the heteroskedasticity and serial correlation tests, the selection of the optimal model was based on the Hausman test. The Hausman test is a statistical test, necessary to select the most appropriate model between fixed and random effects. The null hypothesis (H_0) of this test is that the basic assumption of random effects models holds. As shown in Table 4, from the results of the Hausman test, a p-value = 0.1544 >0.05 is obtained. Therefore, the null hypothesis (H_0) of the test is verified and the random effects model is deemed to be a more appropriate model. Besides, the fact that Model 1 is better than Model 2 is also revealed by the fact that a higher R^2 value is noted in Model 1, as well as by the fact that in Model 2 not all variables turned out to be statistically significant.

Table 4: *Estimation results of the meta-regression models*

Variable	Model 1: Random-effects		Model 2: Fixed-effects	
	Coef. (sd.error)	**p-value**	**Coef. (sd.error)**	**p-value**
(Intercept)	-25.065 (10.493)	0.0169 *		
Dataset_Year	0.012 (0.005)	0.0239 *	-0.008 (0.016)	0.6356
Conference	0.568 (0.269)	0.0346 *		
North_America	-0.322 (0.155)	0.0377 *	0.339 (0.400)	0.3973
Short-haul	0.346 (0.145)	0.0167 *	0.720 (0.217)	0.0011 **
Medium-haul	0.297 (0.159)	0.0624	0.558 (0.214)	0.0098 **
Long-haul	0.440 (0.162)	0.0065 **	0.664 (0.229)	0.0042 **
Short-term	0.535 (0.146)	0.0003 ***	0.545 (0.160)	0.0008 ***
Economy	-0.688 (0.127)	5.6e-08 ***	-0.665 (0.144)	7.1e-06 ***
Airport-pair	-0.394 (0.174)	0.0238 *	-0.844 (0.378)	0.0265 *
INC	0.353 (0.130)	0.0067 **	0.243 (0.168)	0.1505
Frequency	0.744 (0.167)	8.9e-06***	0.675 (0.541)	0.2137
SE_reported	0.439 (0.171)	0.0104 *		
Daily	0.639 (0.296)	0.0311 *		
Linear	0.391 (0.139)	0.0049 **	0.387 (0.167)	0.0214 *
IV	-1.152 (0.143)	7.6e-16***	-1.349 (0.194)	5.4e-11***
Performance measure				
R^2:		0.410		0.340
Adjusted R^2:		0.374		0.160
F-statistic				8.67438, p-value: 2.9884e-13
Chisq:		133.082, p-value: < 2.22e-16		
Diagnostic tests				
Breusch-Godfrey/Wooldridge test:		p-value = 0.827		p-value =0.6269
Homogeneity Q-test:		21.963 (p-value= 0.9968)		
Breusch-Pagan test:	23.677 (p-value = 0.07079)			
Hausman test:	**p-value = 0.1544**			

Looking at Model 1, useful conclusions were generated. The positive sign of the Dataset_Year variable suggests that as the average year of air traffic data in a study increases, the ticket price elasticity of demand increases. Specifically, an increase in the average year of data by 1 year, results in a small increase in the elasticity of +0.012. This positive relationship was expected, from the descriptive statistical analysis, where it was concluded that over time consumers appear to be less sensitive to changes in airline ticket prices.

The Economy dummy is also negative, which means that researchers recorded more negative results for economy-class passengers. This was expected and logical, as when it comes to leisure travel, consumers are considered more sensitive to ticket price, as they aim to maximize the utility of air travel and limit their movements around a certain budget. The positive coefficient of the Short-term dummy is another expected outcome according to the literature, regarding the time horizon of an estimate. When researchers characterize the price elasticities they have calculated as short-term outcomes, fewer negative values are recorded. This is because in the short run, consumers do not have time to adjust to price changes, resulting in more inelastic demand.

All three variables relating to flight distance are positive and statistically significant. Comparing the coefficients, the long-haul dummy has the largest positive influence on the dependent variable and by logic, we would expect the medium-haul dummy to have the next largest influence, which is not the case. This shows that the theoretically predicted decrease in consumer price sensitivity with increasing flight distance due to the relative lack of alternative modes of travel is not entirely correct, as the greater the flight distance, the greater the share of the consumer's disposable income required, which ultimately causes greater sensitivity.

The negative sign of the Airport-pair coefficient indicates that when the demand data of a study are collected at the airport-pair level (connection between two airports), the price elasticity is more negative by -0.394 compared to other data collection levels (National level, multi-airport system, City-pair, etc.). Regarding the demand data of a study, the positive sign of the Daily coefficient indicates that when researchers estimate demand using daily air traffic data, they record fewer negative observations than when using other traffic data (Monthly, Quarterly, Annual, etc.).

Certain results in our model, prove that several choices researchers make regarding the demand model of their study may lead to different results. The positive sign of the INC dummy indicates that when consumer income is included as an explanatory variable in a demand model, the elasticity values are less negative by +0.353. Similar to consumer income, when the demand model includes flight frequency as an explanatory variable, the elasticity values calculated are less negative by +0.744. The SE_reported dummy has also a positive coefficient, which shows that when researchers calculate and report the standard error of their results in their study, less negative elasticity observations are recorded. The positive coefficient of the Linear dummy indicates that when a linear regression model is used for demand, the results recorded are less negative by +0.391 compared to other forms of demand models.

3.3 Sensitivity Analysis

In this section, a few sensitivity graphs were generated to better understand the influence of an explanatory variable on the dependent variable, i.e. the ticket price elasticity of air-travel demand, as predicted by the random-effects model (Model 1). The only continuous variable in the model, the average year of the data collected (Dataset_year), was placed on the horizontal axis, thus, the graphs depict the sensitivity of the dependent variable to the selected explanatory variable as the average year of demand data increases, with all other variables remaining constant.

Figure 9 shows how price elasticities vary over time, by publication type of study. Compared to other publication types (scientific articles, working papers), research presented at conferences appears to have higher (less negative) price elasticities. This suggests that perhaps researchers prefer presenting less negative results at conferences.

Endogeneity is a common phenomenon that occurs in a model when there is an undesirable correlation between a variable and an error term. In Figure 10, the sensitivity is plotted according to whether instrumental variables were used to address endogeneity. When the researcher addresses the problem of Endogeneity in his model, specifically with the help of instrumental variables, price elasticities turn out to be significantly more negative. Therefore, for a better prediction of elasticity, it is advisable not to neglect the problem of endogeneity but to deal with it, ideally with the use of instrumental variables.

The negative sign of the "North_America" dummy in Model 1, indicates that studies that refer to the North American market show more negative price elasticities than other markets in the rest of the world. This classification by Geographical Location (World vs North America) was examined in Figures 11 and 12, for short-haul and long-haul flights, respectively. In conclusion, it appears that when it comes to short-haul flights, North American consumers are marginally less price sensitive to airfare than consumers from the rest of the world. On the other hand, when it comes to long-haul flights, North American consumers are clearly more sensitive to airfare than the rest of the world.

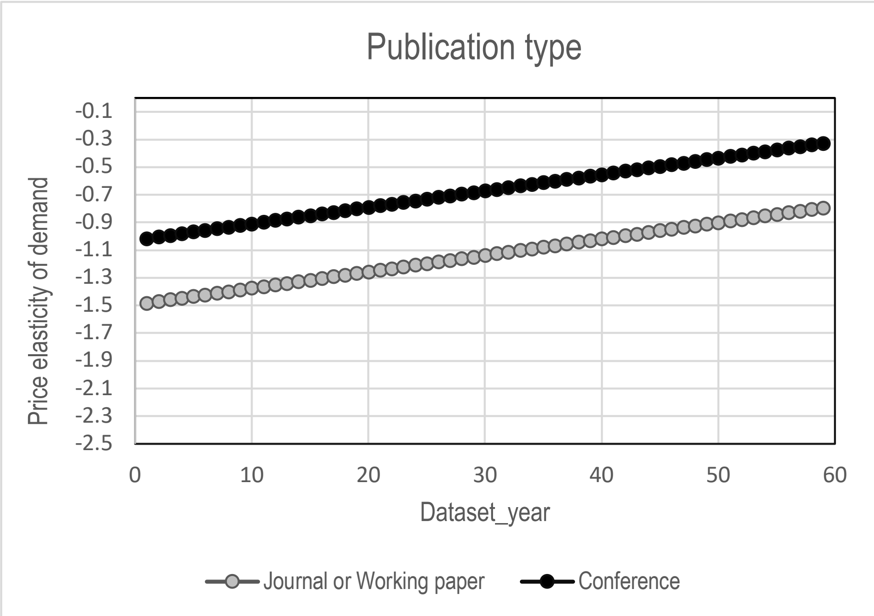

Figure 9: *Sensitivity of the price elasticity of demand to publication type as the average year of demand data increases*

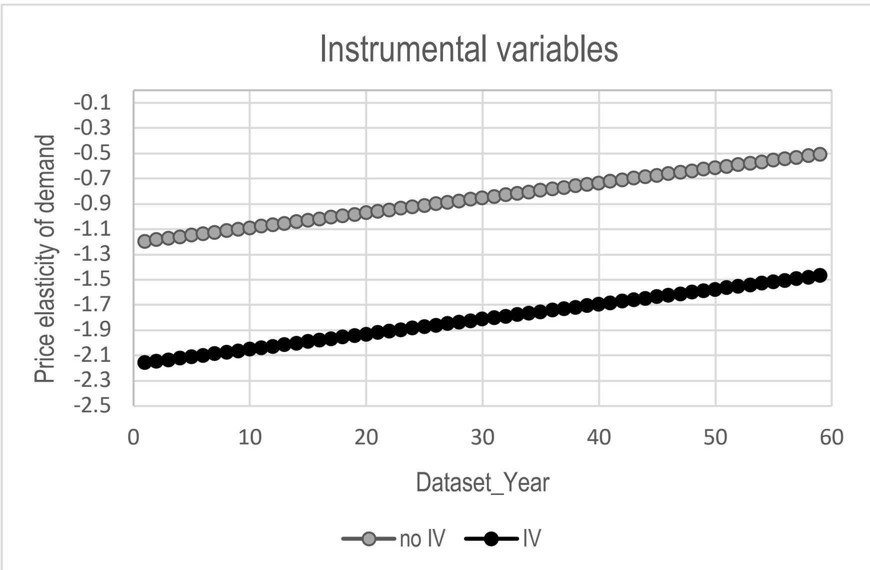

Figure 10*: Sensitivity of the price elasticity of demand to the existence or not of instrumental variables in the demand model as the average year of demand data increases*

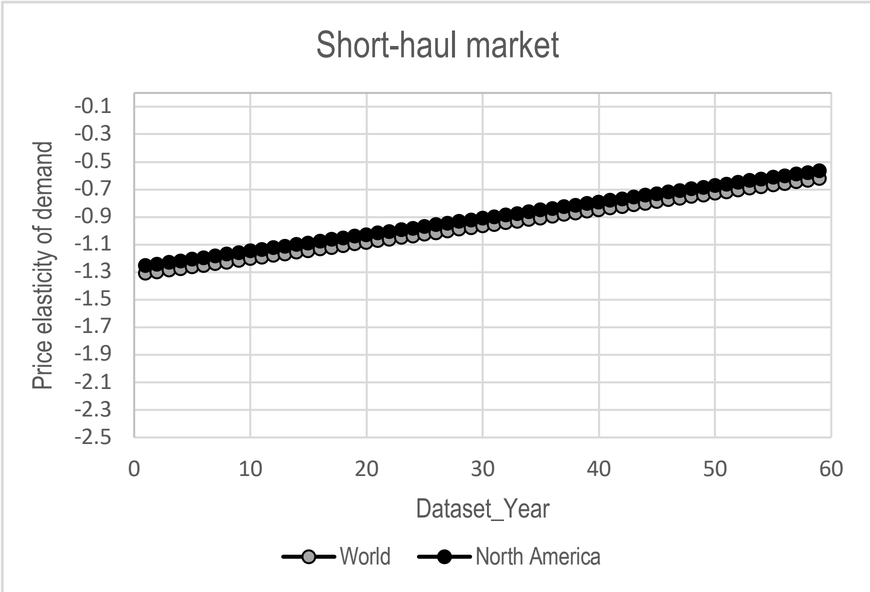

***Figure 11**: Sensitivity of the price elasticity of demand to Geographical Location as the average year of demand data increases (Short-haul market)*

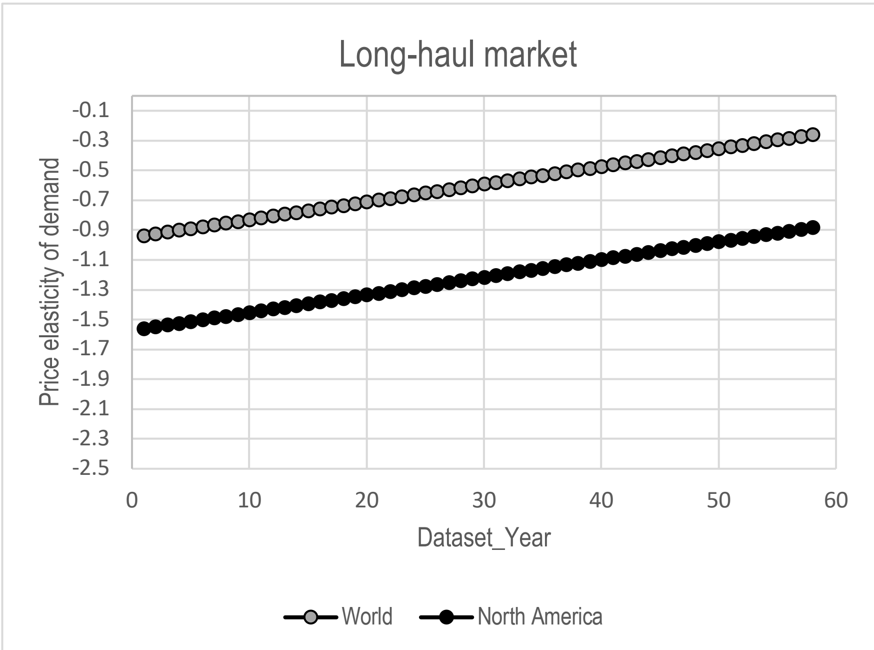

***Figure 12**: Sensitivity of the price elasticity of demand to Geographical Location as the average year of demand data increases (Long-haul market)*

3.4 Heterogeneity Between Studies

To ensure a reliable result, it is important that the individual studies used in a meta-analysis are homogeneous with each other. Statistical heterogeneity refers to the variation in the effect size in question among different studies and is a problem when it is greater than what could be considered a random effect. If a very high degree of heterogeneity is found, then it may be prohibitive to conduct the meta-analysis.

Heterogeneity can be detected visually with the help of a "forest plot", which depicts, all of the effect size estimates recorded for each study in the meta-analysis. This plot shows the extent to which the results of different studies overlap with each other. Results that are far from the other values and therefore do not overlap with other studies are considered heterogeneous and less reliable.

Figure 7 shows the forest plot type diagram, which depicts the variation in price elasticity estimates for the 44 studies involved in the meta-analysis. The studies appear to overlap with each other, except for the study by J. Melville (1998), which recorded an elasticity value of -4.77 for the city-pair link between four countries in the Caribbean region and New York City (for the years 1980-1992). Therefore, the inclusion of this study in the meta-analysis sample may cause a heterogeneity problem.

However, as with any other graph, the visual overview of the "forest plot" is not completely reliable, and heterogeneity testing proceeded with the Q-test during the statistical analysis without removing any study. As shown in Table 4, the p-value is 0.9968>0.05, which means that the model does not show signs of heterogeneity.

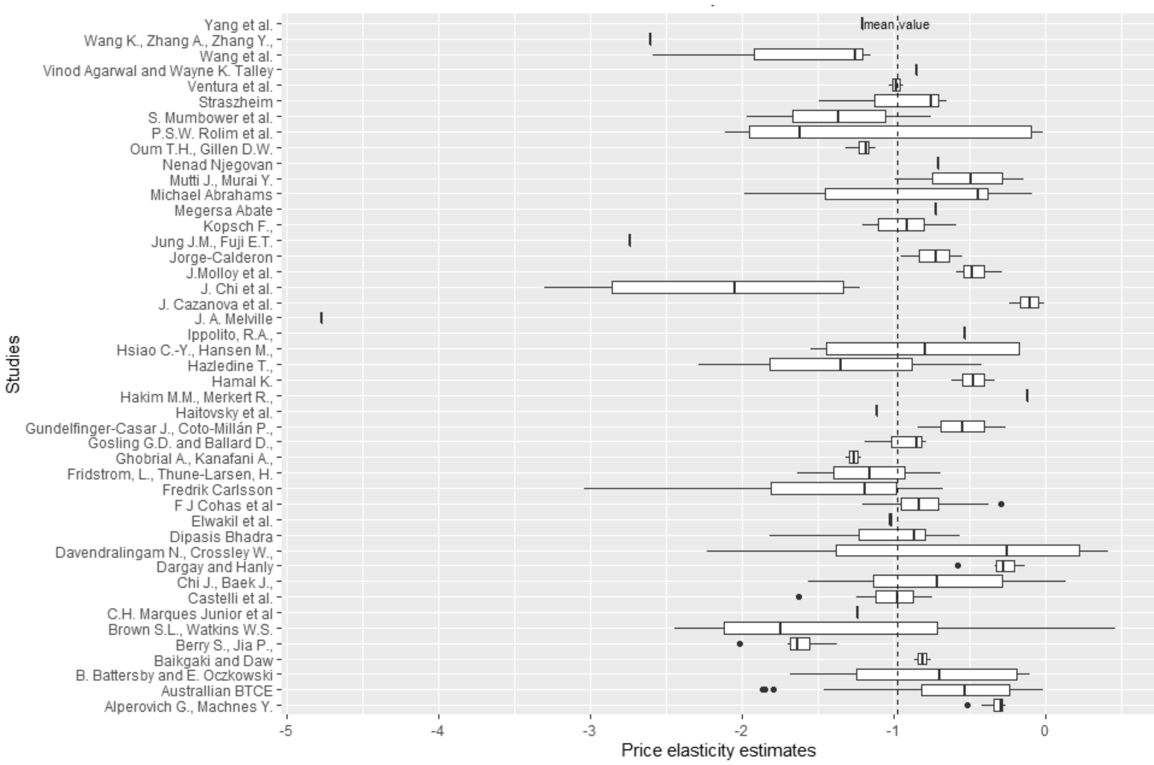

Figure 7: *Forest plot of the 44 studies in the meta-analysis*

3.5 Publication Bias

Publication bias is a phenomenon caused when researchers bias the results they publish. It is no coincidence that studies with "discouraging" results are rare and hard to find compared to studies that provide commonly accepted results. This problem has a significant impact on the reliability of a meta-analysis, as the studies are its sample, and it is important that the selection of studies is not biased. For this reason, it is essential that when conducting a meta-analysis, publication bias is detected to ensure a representative sample of studies that will lead to valid results.

Estimating whether or not there is a publication bias can be easily done with the help of a funnel plot. This is essentially a scatter plot that includes the effect size estimates on the horizontal axis and some measure of precision (sample size, standard error, etc.) on the vertical axis. Because the funnel plot (Figure 8) is required to depict the sample size, 12 studies collected from the systematic review could not be included as they did not contain a recorded sample size.

We observe that the diagram resembles a funnel shape and does not have a particular problem of asymmetry with respect to the mean value, which means that publication bias is not visually apparent. However, there seem to be some gaps, suggesting that some studies are missing. Notably, observations that are far from the mean price elasticity of demand are those with smaller sample sizes and, as a result, lower precision. Clearly, most of the elasticity values are negative with few exceeding zero, all of whom have a low precision index as they are at the bottom of the graph. It is likely that researchers avoid publishing positive elasticity values because they indicate an increase in demand with an increase in airfare, which is considered contradictory. In reality, however, this is perfectly normal and it is very likely that there is an increase in demand with an increase in airfare when it comes to peak periods of a destination, for example, due to a major sporting event that attracts a large volume of tourists.

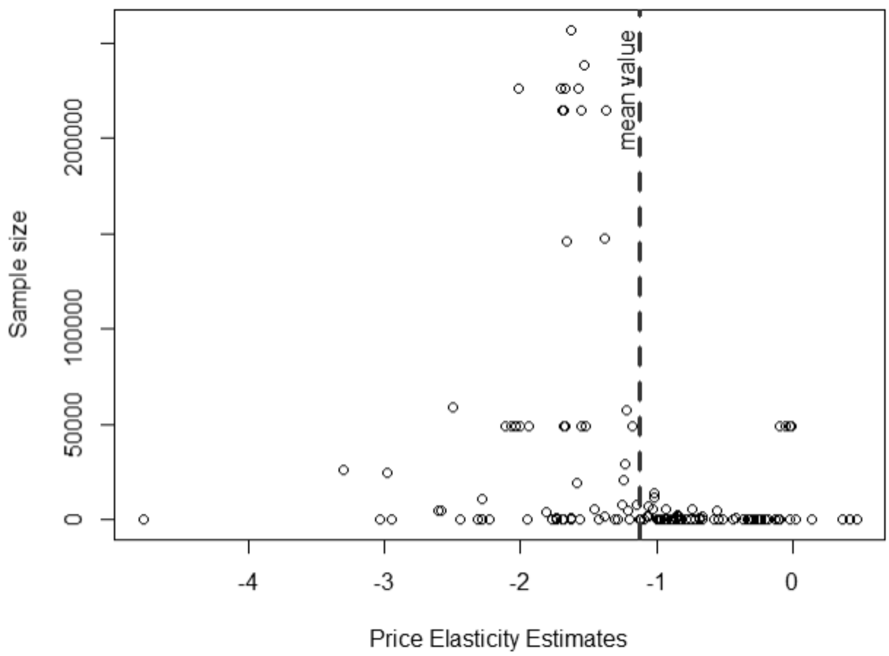

***Figure 8:** Funnel plot for the 32 studies in the meta-analysis*

4. Conclusions

The aim of this meta-analysis is to investigate the determinants to which the variability in the observations in the literature on the ticket price elasticity of air-travel demand is attributed, using the techniques of systematic review and meta-analysis. A systematic review was conducted to collect data, by applying the PRISMA Statement 2020 protocol using the advanced search tool on the Scopus search engine. In total, 258 ticket price elasticities of air-travel demand observations were collected from 44 studies conducted internationally from 1974 to 2020. A descriptive statistical analysis of the data was then performed, where the mean value of all 258 observations of the sample was estimated at -0.97. For the statistical analysis of the data, meta-regression models were developed including a fixed-effects and a random-effects model. The optimal meta-regression model turned out to be the random-effects one, from which we were able to draw several conclusions.

One of the key findings of this meta-analysis was that over time consumers become less sensitive to changes in the price of airline tickets. Time horizon was also proven critical, with short-term price elasticities being less negative compared to long-term elasticities, due to the fact that in the long run, consumers have more time to assess their options and choose what is best for them depending on the situation. These findings should be taken into consideration by aviation authorities when evaluating a new policy (economic, environmental, etc.). As expected, economy class passengers appear to be more price sensitive than business class passengers. It was also proven, that when it comes to short-haul fights North American consumers are slightly less price sensitive to airfare than consumers from the rest of the world. However, when it comes to long-haul flights, North American consumers are much more sensitive to airfare than the rest of the world.

It is also noteworthy that several study descriptive characteristics that refer to the data and the demand model of a study, also turned out to be critical determinants. For example, daily traffic data and linear regression models resulted in less negative elasticities. The use of income and flight distance as explanatory variables in a model also resulted in less negative results. On the other hand, airport-pair data and the use of instrumental variables in a demand model for endogeneity treatment, gave more negative results. Another important fact is that researchers tend to publish less negative price elasticities in conference studies compared to scientific papers or working papers. All of this information is useful to know, for researchers that want to perform a study on this topic, as well as for readers that are interested in examining the findings of a similar study.

Due to limited time and the lack of access to other search engines, the systematic review in this meta-analysis was performed using only the Scopus search engine. It is therefore proposed for future research to extend the systematic review by repeating the advanced search in other search engines such as Google Scholar or Web of Science, in order to enrich the study's sample with more observations. Also, for further research, it is recommended to apply the Weighted Least Squares (WLS) method to the meta-regression models, which allows assigning weights to the different studies based on the precision and number of estimates in the study, so that estimates with higher precision are given more weight since they are more representative of the population. The WLS method, could not apply for the entire sample of this study, since as we saw when checking for publication error, 12 surveys did not include information on the precision measure (sample size). A final suggestion to extend this research is to develop different models for each passenger class category (Economy class model, Business class model, Aggregated model). It would be interesting to see how the models differ by passenger class in terms of the determinants that influence the ticket price elasticity for air-travel demand.

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