Master's degree thesis

LOG950 Logistics

Price elasticity of demand in air passenger transport markets: A meta-analysis

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Preface

This thesis is submitted in partial fulfilment of the requirements for the MSc. Degree in Logistics at Molde University College, specialized University in Logistics, Molde, Norway

The work was conducted in the period between January and June 2015 with PhD. Student Falko Mueller, Molde University College, as supervisor.

This thesis investigates if there is a base price elasticity of air passenger travel demand, and if it can applied to any market. It consist of Introduction, methodological and theoretical chapters, followed by analysis chapter and discussion.

PREFACE AND ACKNOWLEDGEMENTS

First and foremost, we are indebted towards our supervisor, Ph.D student Falko Mueller, for his continuous encouragement and giving valuable suggestions throughout the writing this master thesis. His knowledge, patience, and experience have supported us, and this project immensely.
A special thanks are addressed to Professor Halvard Arntzen and Ph.D student Axel Merkel for a lot of advice, suggestions, and answering related questions.
Finally, we would like to thank our families and friends for their constant support and continuous encouragement through this process.

Thank you.

Abstract/ Summary

Investigating the price sensitivity of air passenger transport demand is often seen as an essential part of economic policy. By examining different markets such as fare class, geographical location and market distance, one can determine how price should be adjusted to attract more consumers. There is much disparity in the estimate for price elasticity of air transport across studies. We seek to examine this disparity with the help of a cross-sectional study where meta-analysis techniques are applied. In total, 443 price elasticities of demand for air passenger travel were collected and analyzed.

The estimated base price elasticity of the aggregated model is -0,789, and the base price elasticity of the leisure model is -1,081. The magnitude of the elasticities will vary depending on the methodology used and estimation choices. The most critical determinants were fare class, geographical location, time horizon, year of the data, and different estimation methods. The publication funnel plot shows that there is a publication bias present, and the authors preferer to report negative estimates compared to positive ones. It is also discovered that the estimates that are more negative then the value –0,8 and a positive estimates over 0,05 report lower precision, meaning that policy-makers should be careful when using macro estimates for basis when deciding on future changes in prices

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Abbreviations

MRA Meta-regression analysis

OLS Ordinary least squares

VFR Visiting friends and relatives

BLUE Best linear and unbiased estimators

GDP Gross domestic product

GNP Gross national product

WLS Weighted least square

1.0 Part 1

1.1 Introduction

Aviation industry has undergone significant changes since its inception. Pels (2008) notes that for decades it was the most regulated among others meaning that airline managers had to follow variety of national, international and bilateral rules and regulations. He also advised that before deregulation there was lack of competition between airline companies, market inefficiency was a commonplace and as a result fares for customers were too high (Pels 2008). According to Widmann, (2016), deregulation of industry in 1978 in USA and major liberalisation in 1997 in Europe was a natural response to growing worldwide population and therefore growing demand for air transport services as the reasonable and fast mean of transportation especially on the long-haul routes. There was a huge need for different markets to be connected with each other. Since that time managers gained freedom in their market activities, marketing decisions, pricing strategies, etc. and the new airline business models evolved providing even more opportunities for passengers (Widmann 2016, Pels 2008, Bitzan and Peoples 2016).

While before deregulation there was literary "one price for everyone", after "opening the skies" between countries and establishing new routes customers got new offers. In fact, with the new affordable prices provided, their socio-economic reasons for traveling (for example, income), motivation and travel behaviour have changed drastically. Market segmentation occurred and understanding what drives the demand in each passenger segment and what factors affect it are very important for the airline managers in their forecasts, product planning and pricing for different segments. Even governments feel the need for this information to implement efficient policies and prices (for example for aviation fuel). One particular study of interest for them is how pricing influence this demand. Doganis (2010) noted that sensitivity of it to fare changes is usually measured by coefficient of elasticity which is always negative. This means that if an airline will rise prices for an air traveling it is expected that demand will go down.

Based on the preliminary research, we find that previous studies were made for various markets, routes, destinations, and segments. Different time periods were observed. Some authors analyzed markets before and after the deregulation; some were interested in a short time scope obtaining observations during six months in a given year, while others adopted data sets for up to 43 years. Despite some similarity in the overall correlation between factors affecting price elasticities reported in the papers, they also provide contrasting results in price elasticity coefficients. It also means that there is no unique base price elasticity that can be used by markets with small statistical adjustments.

Estimating price elasticities in aviation can be a challenge due to different problems regarding data availability on prices, passenger numbers etc. Instead, one can use a combination of different empirical studies to find common factors explaining possible differences in price elasticity. An approach such as this would require conducting a meta-analysis

The thesis consists of two parts. Part 1 introduces the methodology where elaboration of different methods was closer discussed. Then an extensive explanation of data collection and literature review on the concept of elasticity and consumer demand, determinants of air transport demand, in addition to an analysis of articles that reported price elasticity in the different markets were applied, leading up to the formulation of the thesis research questions and expectations. Part 2 consists of the empirical analysis of studies that estimated price elasticity, and the significant predictors for the aggregated, leisure and business transport markets. Part 2 ends with a discussion of the findings and recommendations for further research

1.2 Methodology

This chapter explains which method we used for our analysis, what subject is relevant for this study, and how we performed data collection. In this chapter, we also focus on creating overall transparency to enable the reader to follow the different steps in data collection, methods and models used to give the knowledge to understand how we attained the results. The chapter starts with placing the thesis in terms of the philosophical assumptions as a necessity for further discussion. Next is the research design which provides an extensive overview of various aspects of meta-analysis and issues that can occur using this method and how to overcome them. Then issues related to data collection are discussed and addressed.

1.2.1 **Philosophical assumptions**

Before starting to work on a research project, a researcher must know where they place themselves on the nature of both social science and society (Creswell, 2007). A deeper understanding of philosophical assumptions not only significantly elevate the quality of the project, but also contribute to the researcher's creativity (Easterby-Smith, Thorpe, and Jackson 2015). Burrell and Morgan (1982) developed a 2x2 matrix for researchers to understand sociological theories with the help of paradigms. According to this matrix, we relate our work to the functionalist paradigm, which aims to explain human affairs and believes it can be understood through hypothesis testing and measured via science. The main focus of this paradigm is the assumption that by understanding the status quo of a society, we can provide recommendations within the current structure rather than changing it. Such an assumption corresponds with the future outcome of our master thesis. Moreover, Easterby-Smith, Thorpe, and Jackson (2015) discussed two essential notions that conform to the functionalist paradigm and are relevant for our master thesis. The first one is in the ontological view of realism and points to the fact that there is a single truth that exists together with the facts, and it can be easily revealed. The second reveals the concept of an epistemological view of positivism. According to the authors, epistemology explains how knowledge is a result of precise empirical verification, and its significance should be based on external reality. Whereas traditional positivist research methodology becomes beneficial in deriving the further basis for policies. It stands for the independence of the researcher from what is studied. Thus, there will be no influence on the results, human interests are also not taken into account in this case, generalization of answers are made through the statistical testing (correlation and regression) and for this method a large number of randomly selected observations is needed to obtain significant results (Easterby-Smith, Thorpe, and Jackson 2015).

1.2.2 **Research Design**

"Research is a process of steps used to collect and analyze information to increase our understanding of a topic or issue" (Creswell 2012). The core elements of it are the formulation of the question, collecting data to answer the question, and presenting the answer. Research is vital for adding knowledge and solving issues. In the field of research, it can improve practice by providing researchers and authors with knowledge that enables them to become more efficient professionals. It can also inform policy debates when policymakers are equipped with facts and results, thereby allowing them to weigh in on various economic issues (Creswell 2012). Students who are conducting research for their thesis should become familiar with the existing literature in the field of interest and base their findings on earlier research in the field. This is something we will do in the later chapters of this thesis. Besides, the researcher should transparently present their work so that other academics can trace the steps in data collection and analysis of the information. Because this enables academics to understand how the findings were derived and why the researcher arrived at the respected conclusion. As previously mentioned, the starting point of any analysis should begin by defining the core research questions. Based on the questions themselves, the researcher will have to choose the appropriate type of methodology to collect information in a certain way and to be able to find the answers to these questions.

The primary purpose of our work is to calculate a base price elasticity that can be derived from the previous studies and to define how different variables used in the models impact elasticity estimates. Borenstein, Hedges, and Higgins (2009) suggest that a systematic review can be performed through meta-analysis and regression to test the relationships between multiple variables. Further, they explain how a predetermined system is necessary in order to perform a meta-regression analysis (MRA) to synthesize the overall results. This method includes the process of searching and evaluating the papers that should be included in the research, as well as collecting enough observations from these papers. Thus, considering the procedure, we can state that our master thesis has a quantitative nature.

The following sections provide background for the methodology used in the thesis. The purpose of this is to create transparency and enable the reader to understand and follow the model, and the method applied.

1.2.3 Meta-regression analysis

In 1904 Karl Pearson published a report on "Certain enteric fever inoculation statistics" where he studied the correlation between typhoid and mortality and the inoculation status amongst soldiers in the British Empire. This medical paper was the first on a meta-analysis, which lead to this method becoming used widely and developed in the medical field to aggregate the results in different clinical trials (Shannon, 2008). While it was initially used in the study of medicine and psychology, according to J. Holmgren (2007) it has proved to be a highly effective approach and therefore later spread to other natural sciences.

It is essential to understand that in many cases, a single case study is unrepresentative, and accurate conclusions are not easy to draw from the results. That is why meta-analysis is often defined as "the study of studies" (Stanley and Jarrell, 1989). In other words, it is a method that enables us to conduct "the statistical analysis of a larger collection of results from individual studies for the purpose of integrating the findings" (Glass, Smith, and McGaw 1981, Holmgren 2007). It can present more accurate and credible conclusions about a phenomenon and reduce overall confusion resulted from contradictory findings in the same field from separate studies (Rosenthal 1995). It is a useful tool for evaluating past performances, prevailing experiences in strategy, policy implementing and can be especially useful for countries that are striving towards more international coordinated policies (van den Bergh et al. 1997).

Rosenthal and DiMatteo (2001) state that the basic principles of any good quality MRA are accuracy, simplicity, and clarity. They suggest that it is crucial for the researcher to understand the principles of causality and correlation to be able to explain relationships in the analysis and to stay close to the data to prevent its misinterpretation which in the end may lead to the wrong conclusions. Simple statistical techniques and tools should be favored over the sophisticated ones to be able to estimate accurate results and to answer relevant scientific questions.

Classic meta-analysis consists of five main stages (Cooper, 1998):

1. Problem formulation
2. Data collection (searching the literature)
3. Data evaluation (examination and coding of the literature)
4. Analysis and interpretation
5. Public presentation

MRA starts with defining the topic for the research, formulation of the research questions and hypotheses, as well as determining the dependent variable and the variety of independent ones that may influence it.

Further success of meta-analysis largely depends on the search for all possible studies relevant to the topic. According to Rosenthal (1995), retrieving articles from only one publication source, selecting only major papers and excluding unpublished or non-peered works may result in a biased outcome for which MRA is sometimes criticized. The studies in question must further be able to provide enough information in order to collect observations, code data, and calculate the effect size or the dependent variable. The researcher makes different criteria for including and excluding scientific works as a guide towards which studies are eligible to be incorporated in the meta-analysis and which are not. When the needed observations are found, and their characteristics are collected, the data will then be put through statistical analysis to produce a result for interpretation and further presentation (Cheung 2015).

After an intensive examination of 130 meta-analyses, Nelson et al. (2008) listed two critical features of a complete and satisfactory MRA. The first feature, which is an essential part, is to reference thoroughly to how the retrieving of literature and coding process in the study was conducted (literature reviews, relevant journals, bibliographies, electronic databases, and search engine usage). The second feature is a detailed list of all the primary studies in the sample and a reporting of primary data. Furthermore, in their report, they had proved that a complete MRA must address the issues of data heterogeneity, heteroskedasticity, and non-independent or correlated observations. Especially heteroskedasticity, since this will most likely occur regardless of how the meta-analysis is designed and needs to be treated explicitly. From the study of 130 meta-analyses, they noticed that several studies failed or did not take into consideration different vital things for further validation. Some studies failed to weight the observations or did not report robust estimates of the standard error. Others did not report panel regression models where non-independence is likely to be present or just failed to take into consideration the possibility of cluster data. In many articles, the authors did not include enough regression diagnostic and failed to deal with the issue of publication bias.

The strongest feature of the meta-analysis approach is that it does not define between "good" and "bad" studies but it instead "... provides a replicable statistical framework for summarizing and interpreting the full range of evidence" (Stanley, 2001).

Even though a meta-analysis is a powerful tool, it does not come without weaknesses. An MRA requires a comprehensive search strategy. The quality of the methodology and selections criteria play a substantial part in the validity of the study, in addition to problems like heterogeneity, publication biases and non-independence of the studies that must be identified and dealt. With the help of MRA, one can look deeper into the different studies and understand the reasons for the occurrence of these phenomena.

It can be concluded that MRA is used to identify how specific chosen characteristics like datasets, control variables, samples, estimating methods can influence the reported results. As previously mentioned, MRA can also be prone to non-independence and publication bias, which we are going to address in the following sections.

1.2.4 Publication bias

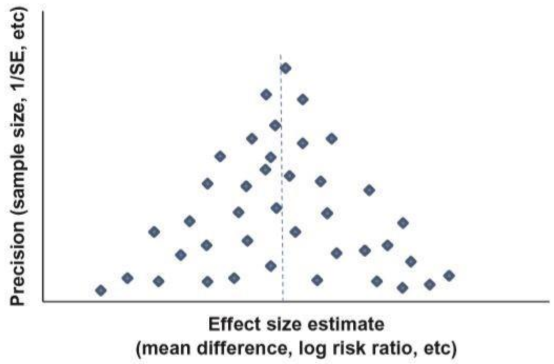
A problem one can encounter when conducting a meta-analysis is publication bias. Publication bias occurs when there is a difference between published (peer-reviewed) - and unpublished (gray paper, non-peer reviewed) studies results. The published studies usually have positive and significant results with low p values, while unpublished studies may have negative or insignificant results. Song et al. (2013) stated that around 50% of completed studies remain unpublished because the authors think they have obtained insignificant results. Therefore, researchers decide not to publish them because they differ from other "acceptable" outcomes and contradict the ones that are strongly predicted by the theory. Borenstein et al. (2009) mentioned that studies reporting low estimates have a lower chance of being published than studies that report high estimates. This situation can discourage researchers from showing their insignificant results and instead lead them to keep their findings to themselves. It becomes one of the reasons why the overall empirical outcome in the field might be more significant than what it should be (Stanley, 2005). If we were only to include published studies in the meta-analysis, the analysis would become biased, and the results would be misleading.

1.2.4.1 How to measure publication bias

In order to prevent publication bias in the study, researchers must know how to measure it and how to treat it if it occurs in the meta-analysis. It is strongly recommended to include an evaluation of publication bias for the meta-analysis in order to convince the reviewer that the results are robust, or to inform of any possible suspected biases. The reason for this is to ensure the integrity of the meta-analysis and the results of the study. Meta-researchers' use three primary techniques for assessing this problem: the funnel plot proposed by Light and Pillemer (1984) and two specially designed statistical tests introduced by Begg and Mazumdar (1994) and Egger et al. (1997).

To detect publication bias, one can compare published and unpublished results from studies that explore the same research question (Song et al., 2013). Using a funnel plot is the easiest way to detect publication bias visually. It is a scatter diagram that shows the studies included in the meta-analysis where precision is on the vertical axis, versus non-standardized effects such as estimated elasticity is on the horizontal axis. Precision can be measured multiple ways, but the most common and precise measurement is the inverse of the standard error (1/SE) (Stanley (2005), p.314). Studies that use small samples are more likely to experience larger sampling errors and will widely spread around the average estimated results. Large-sample studies generally have smaller sampling error and will usually be found in the upper part of the plot, close to the average estimated results.

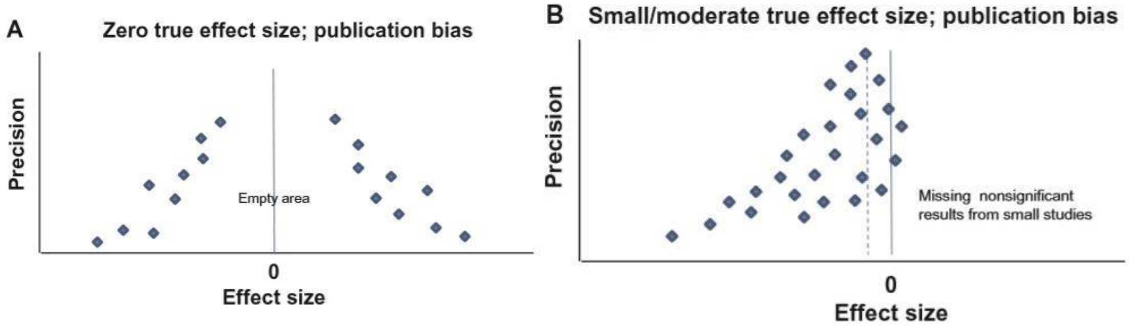
Song, Hooper, and Yk (2013) provide a good visualization of how a scatterplot should look when there is an adequate number of unbiased primary studies. Each point represents an estimated effect size (Figure 1)



Figur 1Funnel-plot visualization with an adequate number of unbiased studies (Source: Song et al. (2013))

When the reported effect size is equal, for example, to zero, the biased selection of studies will produce a funnel plot where the studies reporting more significant outcomes stay distant from the zero or mean effect size as shown in figure2 A.

The funnel plot can also become asymmetric, as it is shown in figure 2 B, in the case, when the authors in their works most often report more negative or positive effect sizes in the field of the study according to the economic theory. Thus, the majority of the effect sizes can be found on one of the sides from the mean effect size reported in the literature.



Figur 2 Figure 2 (plots A,B): Influence of publication bias on funnel plot shape (Source: Song et al. (2013))

1.2.4.2 How to deal with publication bias

Several authors, like Copas (1999), Hedges (1992), Givens, Smith, and Tweedie (1997), in their scientific works proposed quantitative methods to help meta-analyst to correct for the publication bias. These methodologies are used to determine a possible change in the results of MRA after an intentional adjustment by the meta-analyst for the expected effects of publication bias was done. For example, Duval and Tweedie (2000a, 2000b) in their works proposed a nonparametric "trim and fill" method to define the number of possibly missing or unpublished studies in the field, and to estimate the potential effect from these studies. One major drawback of these methods is that they are mathematically complex and require a considerable amount of computation. Moreover, meta-analysts should interpret the obtained result of the possible effect after the adjustment cautiously because the inferences may differ significantly from the initial estimations and in fact, may not be realistic.

Rothstein (2008) suggested that the best way to avoid publication bias is to prevent it. One way to deal with publication bias is to include all unpublished studies or so-called gray literature. To find gray studies, one can run an electronic search without being limited by outcome terms (Song et al., 2013). The problem with finding gray literature such as thesis', dissertations, conference papers, official state documents, technical reports, is that these are not published in journals and are harder to find than published studies. Sometimes the gray literature studies are available online, while other times they must be ordered. In some cases, the last resort in obtaining the necessary literature is contacting the authors directly, although this is something many might find overly time-consuming. (Borenstein, 2009).

In order for our results to be as unbiased as possible, it is crucial that we include all studies and observations of price elasticities available in our dataset. To detect publication bias or systematic heterogeneity, we use a funnel plot to visualize the distribution of the studies against the mean effect size they report in Chapter 8. As we have noted above, further estimation of the potential effect from the unknown studies is very complex, which is within the scope of this master thesis.

1.3 Nonindependence of effects

In a meta-analysis, the reviewers conduct an extensive literature search for primary studies usable for the analysis. An issue that can emerge is the "same author" or "same data" problem that involves finding two or more primary studies by the same author (same author), or that two or more studies use the same data set (same data). Already in the data gathering stage, these issues appear and can lead to between studies dependence (Shin,2009). Often one can encounter same-author studies within the same topic like for example Bhadra (2003), Bhadra (2010), Bhadra and Wells (2005), and in other cases many studies use the same available data sets with some adjustments through the years like BOTE (1986), (BOTCE 1995) which can lead to dependence in effect size. Rose and Stanley (2005) did a meta-analysis on the effect of a common currency on international trade where they noticed that some of the estimates are highly dependent because they were produced by the same author, methods or data set. The possibility of encountering the "same author" issue in the data gathering stage is higher today than what it was before due to increased information sharing.

Shin (2009) explained why the "same author" and "same data" dependency is important to investigate in Cooper (1998) four out of the five-stage meta-analysis process. In the data gathering stage, the meta-analyst wants to find as many primary studies as possible and will often find multiple same-author studies because the authors will often specialize in the same issue. Besides, one will usually find studies that use public data sets that other authors studying the same topic have likely also used. In the data evaluation stage, where the coding of the literature begins, the analyst should list all the studies and then decide whether to include or exclude "same author" and "same data" set studies. In the data analysis stage, the analyst must deal with the issues relating to the choice of excluding all the same author and same data set studies, risking a loss of information.

Alternatively, if the researcher decides to include all the studies, leading to dependency, one must decide how to address the issue subsequently. In order to avoid bias, it is crucial that the analyst ensures that they have generalizable findings by reporting in the results stage how they have addressed the issues related to "same author" and "same data" problem.

In our thesis, we decided to assign to some of the authors their own specific dummy variable. We were not able to find a theory in the literature that discusses this type of approach, but we attained the idea through the discussion with professionals at Høgskolen i Molde. We decided to assign dummies to studies that report 19 estimates and more in order to deal with the dependency issue. We expect that authors that report a large number of elasticities will usually use the same dataset and methods to derive several estimates. This can cause a potential problem because these authors' results then influence the outcome of our regression and "pull" it towards their study specific direction. The idea behind author specific variables is that we will be able to explain how they react with the dependent variable.

1.4 Definition of econometrics and data type

"Econometric is based upon the development of statistical methods for estimating economic relationships, testing economic theories, and evaluating and implementing government and business policy" (Wooldridge 2014). This is a required study field for our master thesis. Knowledge of it is helpful to understand better how the data is organized in the investigated studies, elasticities calculated, dummy variables are chosen and applied, relationships between the variables explained.

There are various types of econometric data (time series, cross-sectional, pooled cross sections, panel or longitudinal data) and it is, therefore, necessary to define what type the researchers are working with to ensure that they are using the appropriate methods for analyzing it.

Wooldridge (2014) denotes that a cross-sectional data set, which is relevant for our master thesis, can be defined as samples from different units such as individuals, firms, cities, and households at any given point in time. Furthermore, the author explains that in cases where analyzing a factor's influence is of particular interest, choosing whether or not to use random sampling is optional (Wooldridge 2014). In our work we are going to compare observations (i.e., price elasticities) provided by different authors and time dimension (that is of high importance, for example, for time series data set) will not be considered.

1.5 Estimation method

Ordinary least squares (OLS) is the most widespread among the estimation methods in the academic literature. It is especially useful for cross-sectional analysis. The use of OLS is justified under the five classical linear model assumptions which create a base for the Gauss-Markov Theorem (Wooldridge 2014):

Assumption No.1: the population or true model with many explanatory variables linear in the parameters and it allows us to "...explicitly control for many other factors that simultaneously affect the dependent variable" (Wooldridge, 2006).

$$y = ß_0 + ß_1 x_1 + ß_2 x_2 + ß_3 x_3 + \ldots\ldots ß_k x_k + \mathcal{U},$$

where:

- ***y*** is a dependent variable and;
- $x_{1\ldots k}$ are the independent variables;
- $ß_{\mathbf{0}}$ is the intercept or constant term;
- $ß_{\mathbf{1}\ldots \boldsymbol{k}}$ are the slope or unknown parameters associated with ***x***, that shows a relationship between ***y*** and $x_{1\ldots k}$

In the literature, the dependent variable is also sometimes named explained, response, predicted, and regressand, while the independent variable is referred to as explanatory, control, predictor, or regressor. In the process of writing this master thesis, these names will be used interchangeably.

The variable *U* in the above equation is the error term or disturbance, which represents additional or unobserved factors that also affect y but are not included in the model.

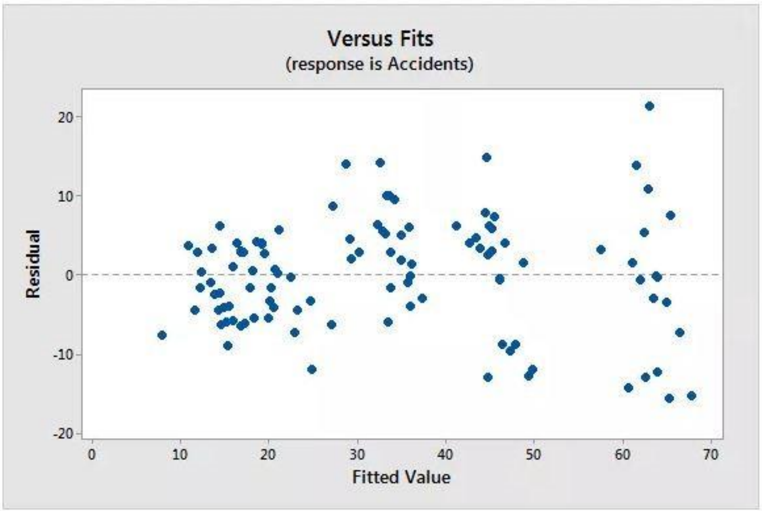
This assumption establishes β_j or *"ceteris paribus"* population effects of x_j on y The definition, according to Wooldridge (2014) is "other relevant factors being equal". For example, if we want to know how inclusion of GDP in the model while simultaneously holding other factors like income, population, frequency, or availability of substitute mode fixed affected the magnitude of the reported price elasticity.

Assumption No.2: a random sample of n observations is considered representative of the overall population.

Assumption No.3: no perfect collinearity occurs in the model. Even though we expect that there might be some correlation between the regressors, this assumption holds when explanatory variables are not perfectly correlated only (i.e., when one of the independent variables in the model is, in fact, the linear combination of any other regressors or same variable but measured in different units).

Assumption No.4: under zero conditional mean value of the error term is expected to be equal to zero for any values of the explanatory variables. If this assumption holds, then the explanatory variables in the model are exogenous or not correlated with the unobserved factors in error *u*. This assumption will be violated in the presence of endogeneity. Also, the assumption will fail if we, for example, exclude an essential variable that explains the dependent variable in the true population model. As a result, an important explanatory variable will end among the other unobserved factors in the error term, and a biased estimation of the population parameters will be obtained.
Assumption No.5: *homoskedasticity* assumption refers to the condition when the error term has the same variance or considered constant for any values of the independent variables. This particular assumption is of high importance for any economic study homoskedasticity assumption refers to the condition when the error term has the same variance or considered constant for any values of the independent variables. This particular assumption is of high importance for any economic study. If this assumption is violated, then one can state that the model suffers from heteroskedasticity. It occurs when the variance of Y given X, is not constant. In other words, heteroskedasticity means unequal scatter where one can notice a systematical change in the spread of the residuals for the span of measured values (Frost 2019)

The problem with heteroscedasticity in an OLS regression is that it violates the assumption that all residuals are taken from a population that is homoscedastic (constant variance). The easiest way to detect heteroskedasticity it through a residual plot. In the plot, the residuals are analysed by fitted values (predicted values) where an increase in both fitted values and the variance of the residuals signalizes the presence of heteroskedasticity. If the plot displays no patterns, then the residuals are uncorrelated. However, if the plot displays patterns such as a cone shape as shown in Figure 3, the assumption of the residuals being homoscedastic is violated and the results will be less precise and cannot be trusted. Estimates that have lower precision have a higher chance that the coefficient estimates are not correctly representative of the population value (Gujarati and Porter, 2009).



Figur 3Residual plot (Source: Frost (2019))

Heteroskedasticity happens more often in datasets that report considerable variation from the smallest to the largest estimates, which makes some models more vulnerable than others. The most common explanation of why heteroscedasticity occurs is because of the omitted variables in the model. The reason to treat heteroskedasticity is to produce more precise estimates that can reflect the coefficient estimates of the population value. Also, OLS is not able to detect this on its own which results in a standard OLS regression producing too small p-values and not representative standard errors which can mislead one to think that the model is statistically significant when it is not. Nelson et al. (2008) suggested that if the meta-analyst uses an OLS, robust standard errors must be applied in order to deal with the heteroskedasticity issue.

The Breusch-Pagan test is applied if the error variance depends on anything that is detectable and is a method that is a more formal way to test for heteroskedasticity than eyeballing a residual plot. If the test shows a $P > 0.05$, then one can consider accepting the H0 that the variance of the residuals is constant at a 95% confidence level. If the $P < 0.05$ one can reject the H0 and accept the H1 that the variance of the residuals is not constant. In order to get the correct standard error, White (1980) developed the test for heteroscedasticity that allows the researchers to derive the reliable inferences and their respective confidence intervals even with the presence of heteroskedasticity. (Gujarati and Porter, 2009)

In our master thesis, we use the OLS method to estimate a linear model. This method enables us to calculate the intercept, of β_0 and the slopes β_1, β_2,... which express the partial effect of the respective explanatory variables x_1, x_2 on the explained variable if we hold other explanatory variables fixed. For example, how the magnitude of the reported elasticities will vary with the inclusion or exclusion of a variety of variables in the model, with the specific study characteristics such a method and treatments applied by the author, time horizon of the elasticity or year of data used. If all five listed and discussed assumptions hold then regression of *y* on *x* with the help of OLS will result in the best linear and unbiased estimators (BLUE) of the true population values with the smallest possible variance. Estimated residuals will also be tested for homoskedasticity using Breusch-Pagan and White's test.

1.6 Data collection

This master thesis aims to analyze and summarise how numerous factors observed in the studies (i.e., geo-economic, service-related and some specific study characteristics) influenced the magnitude and precision of presented price elasticities for the demand for air travel in the literature. Based on this, we focused our attention on searching for the papers that investigated the relationship between the price, other important factors, and the demand. The reported price elasticities in such studies are the dependent variable we need to collect and analyze. In our searching, we knew that it would not be possible to control for publication bias without standard errors. Thus, it was essential to collect papers that reported not only price elasticities but also standard errors or at least t-values in order to calculate standard errors ourselves. The initial search for papers started on the 5th of January, 2019.

In the article of Kopsch (2012) standard errors were not reported, but the author provided the confidence intervals. Standard errors were calculated with the help of the formula SE = (upper limit – lower limit) / 3.92 (Higgins and Green 2011)

Battersby and Oczkowski (2001) provided standard deviations and the number of observations for the estimates. Standard errors were calculated with the help of the formula SE=SD/square root of the number of observations

The data used in this research consists of primary data that was collected in two months period. The main feature of this type of data is that it does not exist in a collected and published form. It means that there is no database on all ever published price elasticities of the demand in aviation transportation. Thus, we had to collect, analyze, and create our data set of the found observations from the very beginning. There are some advantages when talking about collecting primary data. Preparing it usually gives the meta-analyst confidence in the data collection process and further structuring of the observations. This, in turn, leads to better confidence in the overall outcome of the research because the data will be more accurate and will better fit the research objectives. Thus, the quality of the future study is less likely to be jeopardized because there will be direct control from the researcher (Easterby-Smith, Thorpe, and Jackson 2015).

One of the main drawbacks we can name is that searching, collecting, and structuring this data is very time-consuming. As we have mentioned above, it took us about two months to collect the papers in question, to analyze them, and to obtain price elasticities that would become the main observations for our master thesis. The accuracy of any study will mostly be dependent on the sample size adopted. Borenstein, Hedges, and Higgins (2009) denote that the range of it will vary significantly between different scientific works and will be determined by some practical constraints and the type of data needed to be collected. There is no limit to how many observations the researcher can obtain. It is more about "the more – the better" as a larger sample size will be logically more representative of the population and may provide better results (Easterby-Smith, Thorpe, and Jackson 2015). The same was suggested by Harell (2001) who wrote a book on regression modeling strategies, where he mentioned a rule of thumb in model construction. The author states that in order to detect reasonable-size effects with decent power, one must obtain at least 10 or more observation per explanatory variable.

The source for theory for this master thesis mainly comes from textbooks available in the school library, online articles, or existing course books that were acquired earlier during the master program. The data collection on price elasticity and factors are mainly collected on the Internet, either through published articles available in the university's library and online page Oria or electronic sources such as ScienceDirect, ResearchGate, Elsevier, ProQuest, Google Scholar. Relevant search terms/keywords in the English language were used: "demand model", "price elasticity", "aviation transportation", "factors affecting demand", "air travel", "passenger traffic", and their combinations together with some other relevant search terms. Additionally, we have conducted a separate extensive search at JSTOR, Wiley Online Library, Springer Science, and Journal of Transportation Engineering. The reference lists of references from two articles by Gillen, William and Stewart (2003) and Brons et al. (2002) were diligently examined and used as a starting point for the studies collection. However, the authors' reference lists contained studies only from before 2003 and 2002, which means that we needed to make an extensive search on the Internet in order to collect newer papers.

Before downloading the papers, we carefully investigated the abstracts of each study (if the publishing society provided it). The short description of it gave us a better understanding of the topic discussed in the paper, empirical results (if mentioned) and keywords.

Upon obtaining the study, each was immediately visually reviewed. We were interested in methodology, the econometric model itself and reported results in the tables. We also must note that there are differences in the measurement of the demand among the studies and how authors estimate the demand function. Carson, Cenesizoglu, and Parker (2011) divide demand models into two main subgroups: macroscopic and microscopic. In the former subgroup effect size or the dependent variable is represented by an aggregate indicator of air travel in a country or region in question. It can be the number of trips made by the passengers or the passenger revenue miles of country X in a year t that are of interest for the researcher. The latter is related to the demand for air transportation between the studied airports, cities, or on routes. There, analysts are interested in the passenger movements on the predetermined routes or city-pairs. Which of the dependent variables was initially chosen by the author was merely dependent on the purpose of the research and data availability at the time of the start of the demand analysis. In the literature authors define the dependent variable in their models as the annual enplaned origin and destination for passengers between airports (Gosling and Ballard 2019), total number of passengers traveling between countries in years t (Cigliano 1980), the number of passenger-miles of service demanded (Talley and Schwarz-Miller 1988) or the total number of passengers flying with a particular airline (Squalli 2014). The main focus was on the models that considered the number of passengers transported on the left-hand side of the model (i.e., as the dependent variable) and airfare (i.e., as an independent variable) on the right-hand side in a logarithmic functional form as long as we were interested in the reported price elasticities. Studies that contained other model specifications were excluded from further analysis as three other model functional forms - level, level-log, and log-level - don't result in direct elasticity estimates. In some cases, like for example Abrahams (1983) article, we have still included elasticities to our study because the author calculated them with the help of a separate formula so they indeed can be used in our research.

One more essential feature of air travel demand we had to consider was distinguishing it from tourism air travel demand. In general, passenger mix can be divided into four main categories according to their purpose of travel: business, holiday, visiting friends and relatives (VFR) and other purposes (like sport, studies or migration) (Doganis 2010). It is logical to assume that demand that has originated from holidaying travelers (i.e., tourists) may not be representative of the demand in general and excludes the demand from other categories of passengers between the investigated countries or routes. Moreover, the demand is not equally distributed between the two endpoints because the demand pattern shifts towards the endpoint that has cultural, archeological, religious, or recreational importance for travelers. Seetaram (2010) highlighted this issue in his study, where the author provided a critical analysis of airfare elasticities obtained from tourist demand models. The author denoted that apart from the unequal demand distribution between the countries, the price elasticities themselves are unrepresentative because the airfare is one of the many components in the overall cost of the trip for the tourist. The author also states that calculating price elasticities for tourism demand become challenging for the researcher already at the stage of collecting data. Datasets can be prone to measurement errors, and defining the costs of transportation is a tricky procedure. Lots of tourists' preferences and expectations should be considered by the researcher to derive the real price for air travel that is more or less close to reality. It is also a case when an air traveler purchases an "all inclusive" tour, and therefore the real data on the cost of air travel (i.e., data on airfares) becomes unavailable for the study purpose. As a result, researchers adopt consumer price index a substitution for airfares that include prices for all goods that tourists incur at the destination point (air transportation costs, cost of staying at the hotel, car rental, train tickets, taxi fares). Therefore, we excluded studies analyzing the tourist demand from our data collection.

It should also be noted that from the very beginning, we decided that papers employing the stated preference method will not be used for our study. Kroes and Sheldon (1988) explain that the stated preference method is based on the survey of the individuals (air travelers) and determining their preferences and attitudes towards the air travel in specially modeled situations purposely constructed by the researchers. In these articles, the possible demand levels are modeled through the direct observation of the travelers' behavior or through the questionnaires, where the researcher proposes a variety of alternatives and asks the travelers about their possible behavior in the given circumstances (Kroes and Sheldon (1988). As a result, such studies were excluded from the analysis whenever found.

Those papers that made it to the overall set of collected papers were additionally checked for references. With the help of the reference lists, we were able to find some more relevant papers for MRA and literature review. The search stopped on March 15th, 2019.

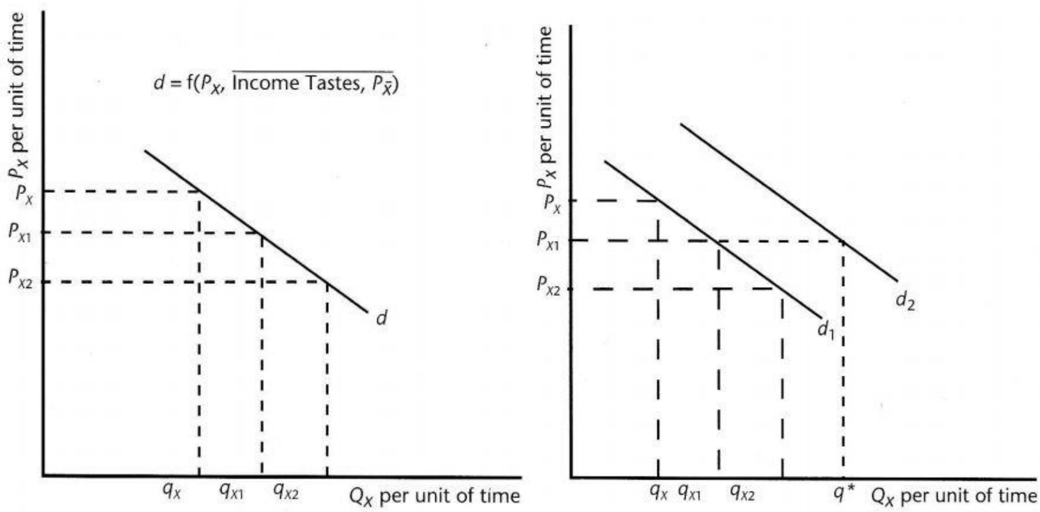
1.7 The concept of elasticity and consumer demand

The purpose of this chapter is to provide the reader with insight into the theory of the consumer's demand, main concept and types of price elasticities related to the demand of a product. In the following paragraphs we will also highlight the classic determinants of the demand from the available economic literature.

1.7.1 Theory of consumer demand

The theory of consumer demand is one of the main elements of microeconomic study. Pindyck and Rubinfeld (2013) denote that the theory is meant to explain consumer's preferences and desires for the goods given the budget constraints present. Studying the choice of a single consumer intends to derive an individual demand function which, in turn, is affected by specific market factors. The ultimate goal of analyzing this problem becomes the theory of demand which establishes the main relationships between price and non-price factors, and the market demand itself. The authors further discuss that this theory explains also individual demand curve that can be further aggregated into the total demand curve of all consumers in a market (Pindyck and Rubinfeld 2013).

Hensher and Brewer (2001) provide a discussion on the importance of understanding the difference between the terms "changes in quantity demanded" and "changes in demand". A good visual representation is given in Figure 4 and Figure 5. The authors explain that the former term explains the relationship between the price of the goods and the quantity of it demanded, holding other factors fixed. With the change in the price, the quantity of a particular good will also change and this will result in the adjusted observations on the same demand curve. The latter term refers to the comparison of two different demand curves by the researcher, and the changes affecting the position of the demand curve itself further up or down are usually brought by the non-price related variables. The interpretation of the demand only through the price prism can lead to misleading conclusions. In fact, given the same price on the market, the changes in demand can be brought by the willingness or the ability of the consumers to pay for this good. For example, as the disposable income of the passengers rises, they start to travel by air more often than usual in a given year. Among other non-price factors, the authors name the personal tastes of the consumers, their age and gender, better service level, improved quality of the goods, and other external factors (Hensher and Brewer 2001).



Figur 4: Left Figure represents the individual demand curve; Right Figure : represents changes in demand (Source: Hensher and Brewer (2001))

It may be concluded that the set of customers' personal preferences and needs can be interpreted as utility values, which in turn determine their choices that further create demand functions from which price elasticity value can be acquired (Gillen, Morrison, and Stewart 2003). Therefore, it is important to discuss the concept of elasticity first.

1.7.2 Concept of elasticity

Concept of elasticity becomes a useful *"unit-free"* tool that allows to measure of sensitivity of different variables to each other when there is some predefined functional relationship between them (Gillen, Morrison, and Stewart 2003). The general formulation can be written as follows:

$\varepsilon = \%\Delta A \,/\, \%\Delta B$, where "$\%\Delta$" denotes a percentage change

Elasticity shows what will be the change in the dependent variable $\boldsymbol{A}$ resulted from a percentage change in an explanatory variable $\boldsymbol{B}$. Values of the price elasticities can be further classified as (Pindyck and Rubinfeld 2013):

1. *inelastic demand*, when the absolute values of elasticity are less than one (or it can be expressed as $\varepsilon > -1$), Indicates that the percentage change in variable B will not affect variable A significantly. The incline of the demand curve in this case may be minimal or almost vertical;

2. *elastic demand* shows opposite relationship. This means that if the absolute values of elasticity are higher than 1 ($\varepsilon < -1$) variable A will be highly responsive to the changes in B and market demand will be represented by the rather flat curve;

3. *isoelastic* demand, when elasticity is constant at every point on the demand curve. A special case of it is the *unit elastic* demand, when elasticity equals to value –1 ($\varepsilon = -1$)

Economists also distinguish three main types of elasticities related of the demand of a product: the own price elasticity of demand, cross-price elasticity of demand and income elasticity of demand (Pindyck and Rubinfeld 2013).

Price elasticity of demand characterizes the percentage change in quantity of the good demanded in response to a 1 percent change in its price (Nicholson 1990). Mathematically it can be expressed as:

$\mathcal{E}_P = \%\Delta Q_x / \%\Delta P_x$,

where $\boldsymbol{Q_x}$ is the quantity of the product $\boldsymbol{x}$ demanded and $\boldsymbol{P_x}$ is the price of product $\boldsymbol{x}$. It is worth mentioning that the classic downward-sloping of the demand function assumes that there is negative correlation between the price and quantity demanded. Therefore, increase in price will negatively affect demand reducing the quantity of the good purchased on the marked and vice versa.

Katz and Rosen (1994) define cross-price elasticity as the percentage change in the quantity demanded of product $\boldsymbol{x}$ by a percentage change in the price of a substitute product $\boldsymbol{y}$. Author says that this type of elasticity can be either positive or negative. The sign gives an understanding whether the goods $\boldsymbol{x}$ or $\boldsymbol{y}$ are substitutes, complements or products that are not related to each other on the market. Mathematically this relationship can be expressed by the formula:

E = $\%\Delta Q_x / \%\Delta P_y$, where $\boldsymbol{P_y}$ is the price of alternative good $\boldsymbol{y}$

The last type of elasticity is the income elasticity of the demand. The definition of it is "...the percentage change in quantity demanded with respect to a percentage change in income" (Katz and Rosen 1994). This relationship can be expressed by the formula:

$\mathcal{E}_I = \%\Delta Q_x \ / \ \%\Delta I$, where $\boldsymbol{I}$ is the income

Price elasticity for the normal or ordinary market product the value is expected to be positive, meaning that higher income results in higher demand for this good or service. In contrast, income elasticity for the inferior or "luxury good" usually is negative (Katz and Rosen 1994).

In order to reduce the confusion, we explain price elasticities magnitudes as "more negative" (i.e., those that are high in absolute values), "less negative" (i.e., those that are lower in absolute values or closer to zero) and "positive" (i.e., those that are positive).

Now that we have defined the concept of elasticity, it seems appropriate to discuss its determinants.

1.7.3 Determinants of own price elasticities of demand

From the theory of consumer demand discussed above we can easily explain some of the basic variations in price elasticities and their determinants.

Nicholson (1990) highlights the idea that the substitution in consumption behavior usually takes time because consumers are not always able to adjust to the situation in a short period. In the short-run time horizon demand will be inelastic compared to the long-run. In the short-run, consumers have to choose basically between the two options. One is to abandon the consumption, and another is to accept the price increase. In many cases, passengers still prefer to travel because they are unable to postpone their voyage or do not have relevant substitute modes of transport. In the long-run time horizon, high airfares may force travelers to look for alternative methods of transportation or even more radical solutions (like relocating their point of destination or changing their working place when it requires frequent travel by air) to reduce their expenditures. In the short-run demand will be inelastic compared to the long-run horizon. This results in the assumption that the time frame is one of the determinants of demand.

The price elasticity of the demand for a good is determined by the availability of alternative substitutes or complementary goods on the market. A low number of alternatives will most likely make the demand inflexible, which will result in inelastic prices. In contrast, a high number of related alternative products will lead to a lower price elasticity because the consumers are less constrained in their choices. An increase in price for one good can make the consumer deliberately buy less of this product or switch to the consumption of another good. Immobility can be a better option due to consumer's current budget constraints. If, for example, prices for travel increases so much that the trip is not "worth the money", then the option of no travel at all could be a better alternative. (Brons et al. 2002).

Commodity's share in the consumer's budget significantly influences the elasticity of the demand. This assumption implies that as the price on a particular commodity rises customers will have to spend a higher proportion of their income, or in some cases even reduce consumption of other products and services to keep consumption at the usual level. Therefore, the more significant the fraction of income needed for purchasing the goods, the more elastic the demand becomes (Katz and Rosen, 1994).

Another determinant of price elasticity of the demand is the market maturity. Graham (2000) discusses in her research five different stages of maturity and concludes that fully a mature market represents an income elasticity that is equal to or below 1 ($\varepsilon_I \leq 1$). It is expected that the higher income provides higher demand from the users' side. However, in this case, most of the consumers already value air travel as an essential commodity that provides no constraints in time and distance rather than as an expensive luxury type of product. The market is characterized by an assumption that consumers already spend a large amount of time flying, and therefore, there will be no significant growth in demand even if the airline companies will lower their airfares.

1.8 Literature review

The purpose of a literature review is to prove that one has knowledge about other studies on the subject, including a domain theory or theories in the field (Baker, 2000). Therefore, this chapter is dedicated to the review of the existing literature that explains various aspects and determinants of air travel demand. Examination of previous studies helps to uncover important variables and factors relevant to our work, as well as methodologies and research techniques that have been used by different authors. In turn, this information will be useful in later explanations of the findings of this master thesis.

1.8.1 Determinants of demand for passenger air transport

In this section, some economic, demographic, and geographic determinants of the demand for passenger air transport and its related price elasticity is discussed.

The demand for air transportation is considered as the derived demand. Travelers use airline services to satisfy their personal needs. For example, it might be seen as part of their trip to a conference (i.e., business activities), tourist destination, or when VFR (i.e., leisure and holiday activities). A variety of customers' activities, in fact, become generators of the demand for air passenger service. Moreover, in the aviation industry, marketers have identified a large number of other factors outside the industry itself that also significantly influences the demand (Doganis 2010).

Doganis (2010), for example, divides factors, applicable for air traveling into two main categories: one that affects all markets in general and another that affects particular routes.

Factors affecting all markets	*Factors affecting particular routes*
Level of personal disposable income	Level of tourist attraction:
Supply conditions:	Scenic/climatic/historical/religious attributes
Fare levels	Adequacy of tourist infrastructure
Speed of air travel	Comparative prices
Convenience of air travel	Exchange rate fluctuations
Level of economic activity/trade	Travel restrictions
Population size and growth rate	Historical/cultural links
Social environment	Earlier population movements
Length of paid holidays	
Attitudes to travel	Current labour flows
	Nature of economic activity

Tabell 1Factors affecting levels and growth of passenger demand (Source: Doganis, 2010)

This author also notes that many airlines conduct personal surveys and market researches to gain knowledge on socio-economic characteristics of air traveling among customers and therefore to understand what drives demand. The number of people traveling (single person or family), time of booking, chosen destinations, profession, age of the passengers, sex, income and any other information gathered is of high importance for their analysis. Additionally, the general needs and behavior patterns of the consumers should be taken into consideration, as different segments tend to have different expectations for their trip, the service available and comfort levels (Doganis 2010). This means that, for example, a better level of service, shorter time of traveling or a non-stop flight may generate higher demand on the same route/destination despite the airlines offering more or less the same price.

During our literature review, we have noticed that depending on the study and data availability, authors have used various independent variables to explain the demand for air travel. The propper systematization of explanatory variables was proposed by Jorge-Calderón (1997). In his work, he grouped them into geo-economic and service-related. The former sub-group is connected to the economic activity of the studied countries, their specific geographical characteristics and includes other factors that are beyond the influence of airline companies. The latter sub-group can be controlled by the airlines because airline companies themselves provide the level and quality of the service and the price of air travel.

In Sivrikaya and Tunç's (2013) research, they took a small sample of 15 related studies and analyzed the number of repetitions of the same variables among them. The analysis revealed that population, GDP, distance, travel time, and price are mostly used by the authors in their models to explain demand variations. These factors are then followed by the GDP per capita and service frequency.

A summary of the collected articles for our MRA somewhat confirms the results of the survey, as mentioned above. As seen in Table 2, among the 68 studies collected, population and income explanatory variables were the most included ones in the models by the authors. The GDP variable was thirdly most important for demand estimation. A frequency variable was added into the models of 18 collected articles. Only in 10 found articles substitute mode of transportation was considered an essential factor affecting the number of air trips made by the travelers on the routes.

Tabell 2occurrence of explanatory variables in the collected studies

Explanatory variable reported in 68 studies	**Occurrence in the study**
Income	38
Population	34
GDP	24
Frequency	18
Airfare	58
Airfare substitute (fuel price, oil price, airline yield/revenue)	10
Substitute modes of transport considered	7

Historically, air transport infrastructure evolved differently from country to country. There are also differences in economic developments, activities, and international trade, which in turn has influenced the number of passenger traffic in each given country. The length and geographic position of the countries/continents also vary. Therefore, the interpretation of elasticities is usually dependent on their connection to a specific geographical location.

A considerable number of papers state that income and population are major determinants of the air travel demand (Abed, Ba-Fail, and Jasimuddin 2001, Abrahams 1983, Anderson and Kraus 1981, Ba-Fail, Abed, and Jasimuddin 2000, Fleming and Ghobrial 1994, Fridström and Thune-Larsen 1989, Ippolito 1981, Mutti and Murai 1977, Srinidhi 2010). Passenger traffic on a route largely depends on the size and distribution of the population (Doganis 2010). It is logical to assume that in densely populated countries and large metropolitan areas demand for air transportation is expected to be significantly higher compared to the demand in smaller countries and some rural areas due to their smaller populations.

In his book, Doganis (2010) denotes that there is a strong relationship between the rate growth in the world's gross domestic product (GDP) and the growth rates in air travel. Growth or decline is expected to be twice as fast as any change in the GDP rates. This statement goes along with the study of Dobruszkes, Lennert, and Van Hamme (2011). The authors applied a "stepwise" regression to determine the most influential factors and concluded that GDP is, in fact, the strongest determinant compared to other highly influential ones that they used in their model: economic decision-power, tourism, and distance. Furthermore, economic activity and trade in any country can negatively or positively affect the demand from air travelers due to levels and growth of their disposable income (Doganis 2010). It is especially noticeable when it comes to developed countries around the world. When comparing more mature markets, we find that a combination of a population's income growing and constant developments and increased efficiency in the air transportation industry results in overall higher demand. China and India are among some of the developing countries where this has occurred (Dresner 2006).

An interesting pattern was discovered during our literature review. Authors implementing income and population seldom consider a GDP or gross national product (GNP) variable in their model and vice versa. Abrahams (1983) is perhaps the only exception, as the author implemented three variables at the same time. In all presented models by him, GNP resulted in insignificant values. The abovementioned issue was addressed by Baikgaki and Daw (2013). They argue that as long as per capita income is obtained by dividing GDP by the population, researchers should strongly avoid the simultaneous combination of them because of multicollinearity.

Some other determinants mentioned in the literature are also worth noting. For example, Bhadra (2012) tested how wealth impacts the demand for air travel, and instead of current income, he employed the ratio of household wealth. Apart from population and GDP already named, Castelli, Ukovich, and Pesenti (2003) also identify distance, tourism, frequency, substitute mode of transportation, aircraft size, and hubbing strategy as further essential and influential factors. Boonekamp, Zuidberg, and Burghouwt (2018) name aviation-dependent employment, ethnicity, public service obligation, and the presence of low-cost airlines on the route.

Depending on the data available and objectives of the study, authors estimate demand and calculate price elasticities for international flights between the countries or continents and domestic flights within the same country. Moreover, this also underlines what type of passengers can be expected on the route. A higher proportion of leisure travelers can be observed on international routes traveling on longer destinations (between countries and continents) while business passengers favor the flexibility of domestic flights. This class of travelers prefers to take early morning trips and return in the evening with the last scheduled flight.

Also, three main markets can be distinguished depending on the distance and time of travel: short-haul, long-haul, and medium-haul. It is expected that travelers will act differently in each of them. Short-haul is considered more elastic because there might be alternative options to choose from which we will address in detail later. If prices rise, geographic region and shorter travel time can cause people to take the bus, car, rail, or boat to the desired destination. The longer the travel distance becomes, the less price sensitive people are due to lack of substitutes and the overall travel time needed. For example, a trip from the UK to the US is not possible to fulfill by car or train, and it is more time consuming by ship, leaving travel by plane as the last option.

Brons et al. (2002) highlight and list multiple levels of substitutes to aviation that play an essential role in demand analysis. One is the substitute between airlines on the same route. If it is homogenous, it will be perfect competition which will result in high price elasticity. If the services and quality offered on the routes differ between the companies, the substitutability will decrease. Another substitution is intra- and inter-modal competition, meaning that on some short-distance routes aircraft will compete with other transportation modes such as boats, cars, or trains. These can provide similar quality and can be considered as alternative substitutes for planes, but whether they are successful or not is dependent on geographical, economic, and demographical factors. For a trip from Paris to London, traveling by car or train might be considered a good option of alternative transport mode when it comes to price, time and geographical placement. A trip that has geographical elements or is time-consuming (long-haul distance travel) can complicate the existing or construction of supply for an efficient substitute mode. On such routes there in almost no inter-modal competition and despite the higher airfares imposed - demand is considered inelastic compared to the short-haul distance trips. The third level of substitutes is different destinations that have similar characteristics. A consumer will have a budget to be used on this destination and expects to get "value for the money spent" on this particular destination. If the fare prices for this destination increases, the consumer will be unsure if the money spent on this trip will be "worth it" depending on the increase in the price. The consumer can instead reconsider the destination and start looking for a substitute destination of similar characteristics that will provide the same "worth" at a lower price (Brons et al., 2002).

Market segmentation, according to the travel purpose, becomes the next strategic determinant. Two main markets are covered in the literature: business and leisure. The motivation for the journey and, therefore, expectations from it differs among market segments. Business-related travel involves meeting with the strategic partners and customers, attending conferences and therefore, it is seen as one of the necessary input activities to further production of other goods and services. Cancellation or postponement of this type of journey can stand on the way of the company's success due to missed opportunities. Thus, in choosing the mode of transportation, they will rely on overall travel time, ticket availability at short notice, as well as convenient departure/arrival times that are highly valued by the business class segment. Moreover, the trip is usually covered by the employer and not by the employees. Therefore, the literature suggests that for business class passengers are time sensitive then price sensitive and demand from this segment is almost price inelastic. The leisure market consists of two broad categories of travelers: holidaying and VFR. These types of passengers usually purchase airline tickets themselves from their budgets. Increasing prices will force travelers to reduce their number of trips, consumption of other goods and services, and vice versa. Furthermore, holidaying and

VFR travelers plan their trips months in advance, and they are not time constrained. In the event of a rise in prices, they may postpone their tour for later, deliberately change their trip destination in favor of lower prices or even cancel it for good. Understanding the difference between them uncovers crucial implications for the airlines that aim to implement effective pricing policies (Doganis 2010, InterVISTAS 2007). For the coding of business and leisure segments, it is essential to know what type of airfare was used by the author in the study. In some cases, like in the works of Battersby (2003), Dargay and Hanly (2001), Granados et al. (2012), it was possible for the authors to obtain fares for different market segments (disaggregated data) where much information is collected. If it was not possible to distinguish between the business and leisure fares, like for example in the study of Srinidhi (2010), aggregated data on all passengers transported by the airlines between two endpoints were used. The main implication is that price elasticities differ in each segment, and it is essential to distinguish between them. Gillen, Morrison, and Stewart (2003) highlighted an idea that those papers that use aggregated data on airfares report less variation in the elasticities and many of the estimates are decreased and with lower standard errors. They further explain that this makes them relatively non-representative of different market segments when trying to investigate the effect of fare changes.

One of the most included variables among service-related ones in the studies is the price of air travel or ticket price. It is worth mentioning that it is not easy to obtain airfare data as it is considered classified. Airlines and state agencies are reluctant to provide it because it gives an insight into the company's pricing policy and opens benchmarking opportunities for potential competitors to improve their financial and service management. As a result, authors obtain this information from multiple sources in an aggregated form, and in some studies, even proxies were chosen instead of real airfare data. For example, Baikgaki and Daw (2013) and Hakim and Merkert (2017) used data on prices of jet fuel, Demirsoy (2012) and Rey, Myro, and Galera (2011) relied on the available data on oil prices. Rolim, Bettini, and Oliveira (2016), Karlaftis and Papastavrou (1998) conducted their study using airline yields per passenger which, for example, may include ancillary revenue (i.e., non-ticket incomes) for the airline company which arises from the additional fees for checked baggage, on-board entertainment or catering that passengers are willing to pay. Therefore, yields are more consistent with the concept of possible substitute or proxy rather than the real airfare.

As it was defined earlier, flight frequency becomes another variable that is often added by the authors in their models. The authors suggest there is a bi-directional relationship between the number of flights offered (i.e., the supply side of the industry) by the airlines and the number of passengers transported (i.e., the demand side of the industry) (Abate (2016), Boonekamp, Zuidberg, and Burghouwt (2018)). Frequency, in general, has a positive effect on the demand because it provides greater flexibility for the travelers, generates more available seats on the route, and provides better convenience of the arrival and departure times. It also helps to uncover the overall distribution of that demand between competing airlines on the market (Doganis 2010). Consequently, lower demand from passengers will force the airline company to reduce the number of flights between endpoints or even cancel their services on the route to reduce costs and to stay profitable.

Aside from the geo-economic and service-related factors mentioned above, there are also some other variables that authors include in their study in the form of dummy variables. For instance, the researcher assigns the dummy for the particular route or destination point that is considered a tourist destination (Abrahams 1983), for a specific day of the week that indicates higher responsiveness of the passengers to price changes (Mumbower, Garrow, and Higgins 2014), or even for specific events such as terror attacks (Park and Koo 2014) or liberalization (Abate 2016) that seem to influence demand.

In this section, we have examined a variety of different variables that authors included in their models to estimate the demand and to produce the price elasticities. This knowledge will further be helpful in our data coding. Moreover, we have found that GDP and income variables should not be used in the model simultaneously because they are both closely related to each other. Thus, we code both variables, but later on, we will merge them in our model into one explanatory dummy variable that will measure the common concept.

1.8.2 Study descriptive determinants of price elasticities

In addition to the primary analysis of the main geo-economic and service-related determinants of air travel that are included in the models, MRA allows us to explain the variation and therefore, the quality of the elasticity estimates between papers with respect to their specific study characteristics. Writing a scientific work requires a unique approach of the author to the choice of estimators, appropriate data sources and structuring, functional forms, and methods for the analysis. There are no uniform guidelines for writing scientific work. Moreover, there are no rules for reporting the results for the studies in the field. Despite some similarities in proceedings and structuring of the papers, every individual work can still be considered as unique. In light of this, a variety of study characteristics should also be addressed by the meta-analyst while conducting MRA. Usually, these factors are controlled for by assigning dummy variables.

Interpretation and quality of the elasticities depend on the next methodological determinants:

Elasticity time-horizon. It is important to distinguish between the long-run and short-run price elasticities. In the short-run travelers are not able to adjust to price changes, and this is reflected in lower price elasticities. In comparison, in long-run price elasticities, travelers can reduce consumption significantly by switching to a substitute mode of transportation (car, train), relocating and changing their workplace to reduce their expenditures and travel by airlines less.

Data level aggregation. In scientific papers, the data used is usually aggregated on the national or route level. It is reasonable to assume that the demand for air transportation services of the whole country will differ significantly from the demand that was formed on a specific route because diverse influential factors should be considered in each case. Previous research suggests that price elasticities reported in the studies that use national/regional aggregated data levels are expected to be lower compared to estimations obtained for the route level. The main explanation of this is that, for example, with the rise of the departure tax on the national level all routes will be equally affected and therefore passengers will not be able to avoid an increase in airfares. Demand is relatively inelastic. On the other hand, higher airport charges for using their facilities will force all serving airlines on the route to raise their ticket prices, making the cost of the journey more expensive. In this situation, the demand is relatively elastic as it may be naturally diverted to other destinations, especially when it comes to the leisure segment. Moreover, travelers may seek out substitution from other modes of transportation wherever possible to avoid high expenditures (InterVISTAS 2007, IATA 2008)

Publication type. It plays an essential role in the quality of the price elasticities. Peer-reviewed works are considered to be a more reliable source of information since they were initially checked by other researchers published in a reputable journal. Non-published works or "gray literature" usually consist of conference reports, working papers, master thesis' or any other sources that were not peer-reviewed and accepted for further publication. What mainly distinguishes them from each other is the fact that published journals usually report price elasticities close to those that go along with the theory. In contrast, non-peered papers tend to provide lower or higher elasticities in the same study field.

Year of data collection. The data collection period can additionally uncover the extent of variation in price elasticities among the articles with the time. For example, liberalization that occurred back in the 1990s in aviation (according to Doganis (2010) the US market was fully liberalized after 1992; in Europe and some other countries deregulation came into force from 1997) had strong positive effects on the industry by bringing new perspectives, and at the same time opened new opportunities for the travelers in terms of routes, prices and service level. This fact suggests that those papers that were published before the liberalization might report higher price elasticities than those that used newer or up to date data sets.

Data type. Data usually comes in four main types: time-series, cross-sectional, panel, and pooled. Time-series data is the most commonly used type among authors for estimation of price elasticities because it helps observe price, income, and demand changes over many years. This is also expected, considering the developments in the aviation industry. Time series data enables the researcher to build two types of models: static and dynamic. Elasticity estimates from the static model are usually considered short-run elasticities, while with the help of lagged exogenous variables in the dynamic model long-run elasticities can be obtained. Estimates derived from the cross-sectional analysis, in general, are interpreted as the long-run elasticities. According to Fearnley and Bekken (2005), observations are viewed as the equilibrium situations of the fare, frequency, or income levels. One year is enough for travelers to adjust to the changes in price if needed. More recent papers prefer to use panel or pooled data which have characteristics of time-series and cross-sectional type.

Functional form. The double log-linear functional form is the most common among the papers that estimate price elasticities. However, some authors studying the demand have not been interested in deriving price elasticities. They adopt other functional forms in their work but still report elasticity estimates because it is possible to derive them from the separate formulas.

Method applied in the study. Depending on the data type and study objectives, there are many methods available to perform regression and to produce results. The purpose of the method variable is to analyze whether methodology influences the heterogeneity and quality of the reported elasticities among the studies.

Standard error reported. The standard error is a measurement of the variability in the estimate, and it provides information on how precise and reliable the estimate is. It is unknown why some researchers do not report the standard error for the estimate, but a theory is that the author might have found results with high variation. Thus, by removing the information about the precision of the results, the author may increase the likelihood of it being published even though the results may not be significant or reliable.

Stationarity. In time series analysis data is considered stationary when the parameters of the data that generate the process remain unchanged over time. The fundamental assumption is that means, and standard deviations should be constant for all random variables, which implies that there is no trend in the data. When working with non-stationary data, most of the statistical tools become useless, as well as the following results themselves being spurious. This problem was first addressed in the work of the researchers Granger and Newbold (1974). The authors stated that regression with non-stationary time-series data usually provides highly significant coefficients and high values of R-square, which demonstrates the overall goodness of fit of the built model. They denote that the results are considered meaningful, whereas there is no existent relationship between the variables in the model and the proposed outcome is more likely unrepresentative of the objectives of the study because it is based on the different assumptions. We expect that some earlier studies with time series analysis are prone to these kinds of spurious regressions because it was not common among authors to test for stationarity, not to mention to use methods for the treatment of non-stationary data. Therefore, it is interesting to test whether there is any variation among the reported elasticities.

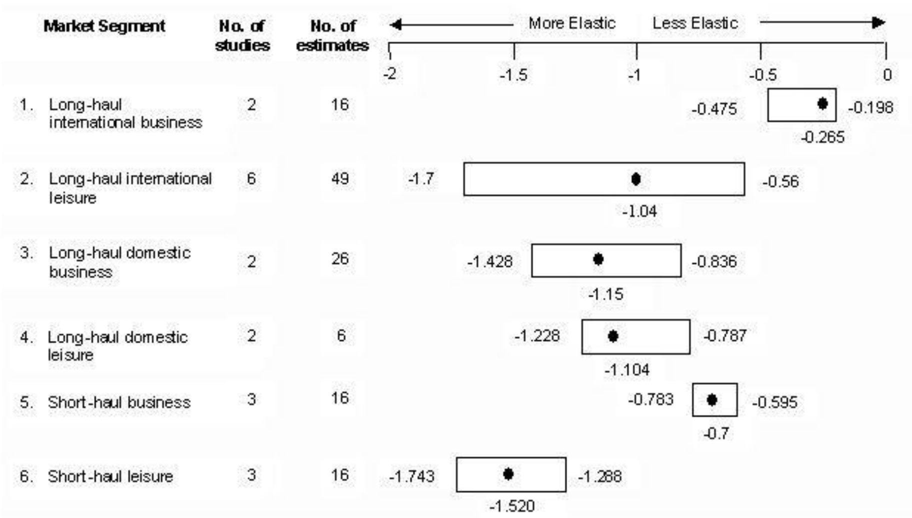
Endogeneity. This problem is closely related to the reverse causality, meaning that in economic models of the demand for air transportation, there are not always independent variables affecting the dependent variable, but vice versa. For example, it is believed that demand responds to price changes in the market. Although on some routes, passenger traffic may not respond to deliberate price increases from airlines because the destination is considered popular among travelers. At the same time, significantly low passenger traffic may encourage airline companies to reduce prices for transportation due to unforeseen economic and political situations or seasonal patterns influencing the demand. In the latter case, to save costs and to stay profitable airlines will likely reduce the number of overall flights between the origin and destination points. These examples show that reverse causality also exists between the demand and supply side of the industry. There is no doubt that higher frequency is an excellent stimulator of the demand because it provides more opportunities for passengers, especially for the business segment that values convenient times of departure and arrival. Nevertheless, there is no point in arranging additional flights on the routes where demand is moderate or low. Endogeneity is also related to the condition when any of the independent variables are correlated with the error term (i.e., factors that are not included in the model). One of the underlying conditional assumptions states that the regressors are exogenous and error term should be equal to zero in this case. In the presence of endogeneity, this assumption will be violated as well as the consistency of the estimators. In scientific papers, some authors address endogeneity as a problem and treat it accordingly in their studies. Others completely ignore this issue, and in these cases, it is expected that the reported elasticities may be underestimated.

1.8.3 Literature review of the reported elasticities – article's review

This section aims to summarize and present price elasticities previously reported in the studies. Taking into account the main objectives of our master thesis, we have performed a literature review to summarise and present findings for different markets, highlight specific conditions, as well as characteristics and facts about each of them. We will use this information during subsequent comparisons with our own findings.

A research paper from 2003 by Gillen, Morrison, and Stewart (2003) has been especially relevant for our thesis. In this work, the authors were some of the first to try to generalize price elasticities to give managers a better understanding of how their customers react to prices, as well as providing governments with the information they can use in future policymaking. They conducted a detailed study of price and income elasticities of demand for international and domestic short-haul and long-haul trips and included market segmentation (business and leisure travelers). The authors analyzed 21 studies and gathered 257 estimates on the price elasticity of demand. Their case report states that there is indeed a significant difference between the routes, segments, and travel distances when it comes to elasticity values. For example, long-haul international business/leisure destinations are characterized by the less negative elasticities at -0.265 and -1.04 (compared to long-haul domestic business and leisure routes) mostly because there are no other efficient substitute means of transportation for all types of travelers to get from point

A to point B. Business passengers, as was expected, are less sensitive to fares. Their trips are mostly paid for by the firms they are working for and time is highly valued, resulting in these passengers being inelastic on short- and medium-haul markets at -0.730. At the same time, leisure travelers will be more price sensitive at -1.520 (especially on the domestic routes) as they prefer to plan their trips in advance and book tickets when fares are relatively low. They may even choose another destination for holidaying if the cost of the trip becomes too high (Gillen, Morrison, and Stewart 2003). The chart adopted from the authors' work provides an insight to the results obtained by the authors:



Tabell 3Chart 1: Own-Price Elasticities of Demand (Source: Gillen, Morrison, and Stewart, 2003)

Another rather interesting study by Brons et al. (2002) where the authors analyzed how knowledge of price elasticities based on the literature and articles way back from 1974 to 2000 can benefit governments in their implementation of environmental policies in the future. In their meta-analysis, they examined how variables such as GDP levels, distance and destination, geographic scope (North America, Europe, Australia, Intercontinental), passenger segmentation, elasticity time horizon and data collection period affect price elasticity of demand. In total, they used 37 studies from which they gathered 204 observations ranging from the most negative found at –3.20 up to the highest positive at +0.21 (mean price elasticity from all studies resulted at –1.146). Descriptive statistics were used to explain variations in the chosen estimates, followed by a meta-regression analysis. It showed that from a theoretical point of view, long-run price elasticities were much higher in absolute value. The authors point to the fact that implemented policy will be more effective if the long-run horizon is considered and the policies are based on long-run elasticities rather than short-run. Additionally, they state that with time, especially after the deregulation period, travelers became less sensitive to price as the low-cost airline carriers introduced new and more affordable fares. If there is no substitute for long-haul trips, demand is also relatively less responsive, and price elasticity is rather low (Brons et al. 2002).

Mumbower, Garrow, and Higgins (2014) based their study on American low-cost airline JetBlue and provided an insight into how the price elasticities can be calculated and implemented by gathering online data from advanced bookings for flights (total number of 7500), departure days and times and booking days. They also discussed how and when companies could implement promotional sales with greater success. In general, their study shows that as the date of departure approaches from 22-28 days to 1-2 days, customers become less sensitive to price and price elasticity decreases from -1.89 to -1.57, respectively. They note that, in the case of the abovementioned airline, customers were less sensitive to price on Mondays and Tuesdays (price elasticities are -1.12 and -1.09 respectively). Based on this it could be reasonable for an airline to start a promotion from Wednesday to Sunday when customers become more price sensitive and demand elasticity increases up to -1.85 (Mumbower, Garrow, and Higgins 2014).

A similar study was done by Morlotti et al. (2017) for the UK market. Their analysis was based on observations taken from the low-cost caeasyJet. Internet fares were analyzed on 21 routes from Amsterdam Schiphol Airport over six months period back in 2015. They concluded that this airline targets more business passengers than holiday travelers and report price elasticity at –0.753. Demand was inelastic 1-2 days before the trip, and most of the bookings were made during weekdays when price elasticity was the lowest compared to weekends. The authors also found that during summer months (especially July) price elasticity was slightly more negative at -0.809 because the number of price-sensitive leisure travelers grew significantly on the routes that the airline served meaning that seasonality also affects demand (Morlotti et al. 2017).

Park and Koo (2014) analyzed factors that affect demand for US airline transportation in general. Among them, they studied passenger and airline behavior, seasonality, unexpected events (Twin Towers 9/11 attack), and mergers between 5 major US carriers. In their paper, they calculated price elasticities for them that vary between the more negative one of -1.893 for US Airways and the less negative of -0.298 for United Airlines. Cross price elasticities provided in the paper imply that there is a high level of competition between some US carriers, especially on specific routes and destinations.

Authors concluded that fares imposed by the airlines, the income of passengers, seasonality, and merges in the industry indeed influence demand for air transportation (Park and Koo 2014).

Abrahams (1983) presented an econometric model for the US domestic market during the 1973-1977 (i.e., before the deregulation of the aviation industry). Unlike his predecessors, who mostly discussed geo-economic factors in their work, this author revealed essential concepts such as quality of service and intermodal competition on the routes. Coefficients were obtained from the pooled time series and cross-sectional data, and elasticities were further calculated with the help of a separate mathematical equation. For transcontinental city-pairs (i.e., long-haul US domestic market) short-run price elasticity is -0.44 while the long-run is -1,81. For the medium-haul market, they obtained a value of – 1.22 and for short-haul -0,36. They concluded that the demand for air travel is highly responsive to airfares. The longer the distance of the trip becomes, the more inelastic the demand becomes compared to the short- and long-haul markets. Moreover, long-run price elasticities more than double in the long term.

Oum, Waters, and Yong (1990) conducted an extensive survey of the estimates of price elasticities of demand for transport among published papers between 1974-1990. They collected and reviewed 70 estimates for a variety of transport modes (air, road, or sea) and markets. In their work, they discussed the concepts of elasticity for passenger and freight markets. The main findings of this report go along with the classic theory in the literature that in general, the demand from the business segment is inelastic compared to the leisure segment. Aside from this, they discovered a pattern in the elasticities, noting that those obtained from the cross-section data are typically higher than those from time-series data analysis.

Jorge-Calderón (1997) proposed an econometric model for scheduled air serviced in the entire network of European international routes in 1989. In this study, the author analyzed specific European geo-economic characteristics of the demand and patterns of airline services. The collected data was intentionally divided into three main sub-samples depending on the length between the origin and destination points to address the possibility of intermodal competition on the routes. Average economy fare data was used to estimate demand. Their results suggest that on the shorter market distances (below 600 km) demand is inelastic, resulting in the elasticity of -0,72, and as the distance of travel increases (from 601-1200 km) price elasticity becomes more negative at -0,96. Moreover, the author confirmed the fact that the European short-haul market is quite sensitive to flight frequency, suggesting that a large proportion of business class passengers travel on the given routes.

Abate (2016) provided an insight into the route-based travel demand elasticities in Africa in the period spanning from 2000 to2005. The author collected panel data on 20 city-pair routes to and from Addis Ababa. Apart from the geo-economic and service-related factors, the author was interested in the effect of liberalization on the thin markets like African. His results confirmed the hypothesis that this market is characterized by low supply efficiency meaning that in case of excess demand they will prefer to raise prices to adjust the number of passengers to the available seat capacity or even purposely benefit additional profit from short-term demand spikes. He concluded that further liberalization would positively affect demand. Deregulation and less strict policies from the government's side would bring competition between the airlines on the routes to a new level. It is expected that airfares would be lower, providing a better level of services and more opportunities for travelers. Airlines, passengers, and economies of African countries are expected to benefit significantly from the developments in the industry. Meanwhile, air travel is still considered as the luxurious service and reported elasticity in the study is -0,719, which implies inelastic demand on most of the routes in 2000-2005.

The Australian market was studied in detail through the years by the Bureau of Transport Economics. Among articles collected for our master thesis analysis, we have working papers by Smith and Toms (1978), Saad et al. (1983), BOTE (1986) and BOTCE (1995). The most recent study, among them, dated 1995, presents elasticity estimations on international routes to and from Australia (12 markets in total). Time-series data were collected for the period 1986-1993 and disaggregated by the travel purpose on the long-haul market. The results of their comprehensive study suggest that price and income are the most significant determinants of Australian leisure travel. The average airfare elasticity for the leisure market from Australia is -1.8 and -1,85 for travelers that visit Australia from other international countries. For the business segment, the average price elasticity between -1,2 from Australia and -1,0 for the business visitors arriving from other countries.

Hakim and Merkert (2017) provided an econometric analysis of the demand among eight South Asian countries (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka) for a period of 43 years (1973-2015). They stated that income, foreign direct investments, flight frequency, and jet fuel price (as a proxy for the price of air travel) are the significant determining factors in estimating the demand for low-income countries. Moreover, the number of passengers more than double with the increase in personal disposable incomes. In the event of unexpected growth in demand, the main obstacle may occur on the supply side of the industry. A solution requires significant developments in the infrastructure and higher customer orientation from the airline companies by providing more available seats on the routes and frequent flights.

Based on the preliminary research, we find that previous studies were made for various markets, routes, destinations, and segments. Different time periods were observed. Some authors analyzed markets before and after the deregulation; some were interested in a short time scope obtaining observations during six months in a given year, while others adopted data sets for up to 43 years. Despite some similarity in the overall correlation between factors affecting price elasticities reported in the papers, they also provide contrasting results in price elasticity coefficients. It also means that there is no unique base price elasticity that can be used by markets with small statistical adjustments.

1.9 Expectations, Research questions and Implications

Based on the literature review, we have formulated the following research questions for the present study:

RQ1: Is there a base price elasticity of demand in air passenger transportation?

The objective of this study is to obtain an intercept, or beta 0, in the model, which should be interpreted as the base price elasticity when the rest of the variables in the model are equal to zero. The model will have a "base case" that will create the platform for estimation of the base price elasticity. The "base case" will include the control variables that have specific characteristics other than the variables presented in the regression output. Any possible combination of the intercept with the other variables by adding the adjusted coefficient from the model will produce a new value.

If it does exist and can be calculated, then the next questions worth answering will be:

RQ2: What is the price base-elasticity of air transportation that can be applied by any market?

The literature review suggests that, in general, price elasticities can be categorized according to the geographic area for which they were estimated, market distance, the purpose of travel. Therefore, apart from striving to obtain a reasonable base price elasticity, we would like to estimate the model that will have adjusting coefficients that together with the base elasticity will create a new variable. For example, if a base case will represent the European continent, then by summing the intercept with the adjusting coefficient produced for the North American continent, one can obtain an elasticity for the latter geographic market. Alternatively, if a business class passengers will be considered in the base case then by summing intercept with the adjusting coefficient for the leisure segment, a researcher can obtain an elasticity for the latter category of travelers.

While answering this question, the expectations were set in accordance with the theory provided in the literature. Therefore, we expect:

1. to find estimates related to the business class passengers less negative compared to leisure class;

2. that long-run estimates will result in the estimates that are more negative then short-run;

3. that on the route level price elasticity will be more negative compared to the national level; 4. that short-haul market elasticity will be more negative then elasticities for medium-haul and long haul.

RQ3: What influencing factors are relevant determinants of price elasticity estimates from previous studies?

It is interesting to look closely at how the inclusion of geo-economic, service-related, and considering some specific study descriptive determinants influence the magnitude of the reported elasticities among the studies.

It is also worth mentioning that in some cases, the economic theory can easily be linked to the discussion of the magnitude of the price elasticity or explanation of the relationship between the control and predicted variable. This information may be relevant for the decision-makers, regulators, aviation industry players, in their investigation and analysis, policy implementation and better marketing strategies. The interpretation of regressors (i.e., with respect to the methodology and type of data used, inclusion/exclusion of the geo-economic variables in the model, and some others) should only guide the authors in conducting their studies in the future. This means that the information may be valuable in a way that it will provide an insight into what is already known or done in the field, enabling researchers to compare different estimation methods applied by other authors in the past and choose an appropriate one to get valuable results.

2.0 Part 2.

The following chapters represent the analysis part of this master thesis. At first, we proceed with the data summary and review, where we present descriptive statistics of the collected elasticities and discuss how the data was collected and coded. Then, we introduce a conceptual meta-regression model. Further, we provide a discussion about the building and estimation of different models (i.e., aggregated, leisure, business) and present outputs from the regression. Later on, we address the issue of publication bias by presenting a funnel plot as the visual depiction of a systematic heterogeneity and provide some discussion on the topic.

2.1 Data analysis

This chapter of master thesis is dedicated to the analysis of the data. In the following sections we present a summary of the collected articles, and related descriptive statistics to uncover some variation among the reported price elasticities. Here we explain proceedings in searching and and provide some additional explanations to the coding of the data.

2.1.1 Summary of the literature

In order to conduct a meta-analysis, we have performed a comprehensive search for existing literature on the price elasticity of passenger air transport demand. Givens, Smith, and Tweedie (1997) study, Brons et al. (2002) and Gallet and Doucouliagos (2014) meta-analysis' on price elasticities became a starting point for our master thesis. Initially, we have analyzed the reference lists of papers the authors collected. Later, we expanded our search to the biggest publishing societies and some journals that were focused entirely on the articles related to the transportation industry. In total, we have collected 219 articles. From this set, only 68 papers created the basis of our master thesis. Further analysis of the final collection resulted in 443 observations. Appendix A gives an overview of the collected articles and their characteristics such as publication type, geographical scope, year of data, number of observations reported, mean estimates and range of estimates. From this set, 12 papers are either thesis', conference or working papers, meaning that they are non-peered.

From the total set of price elasticities collected, only 326 observations were significant, 117 elasticities were either insignificant or authors did not report any information, and for 91 estimates the authors did not report neither t-values, nor standard errors. The main number of elasticities were negative and only 13 observations were positive. The most negative elasticity found is -3,54 and the highest is positive 0,89. The standard deviation of the elasticity distribution is 0,735. On average 6 variables were used in the model by the authors. The total data set of the studies covered the period from 1946 to 2016.

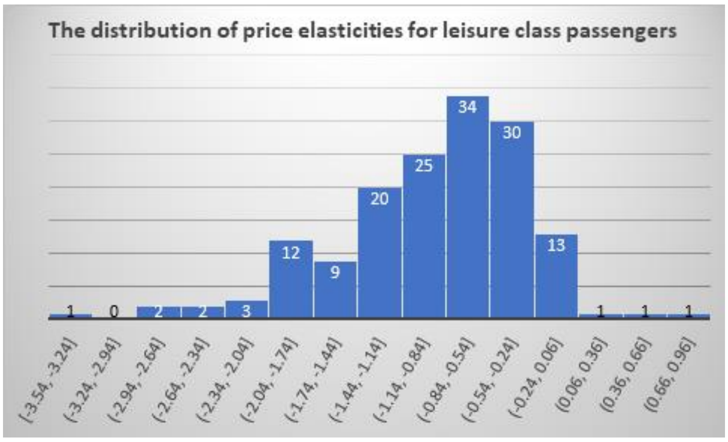
2.1.2 Descriptive statistics

Before we proceed with the presentation and explanation of the meta-regression results, we would like to present an illustration of some descriptive statistics of the collected price elasticities.

The statistics Charts 2-4 represent the distribution of elasticities for business and leisure segments, and both segments combined. It is evident that in general, the distribution of price elasticities for the business class passengers among the collected studies shows that the demand for this segment is inelastic. Among the 45 collected estimates for this class, the most negative estimate found is slightly over –1.1 while the highest positive is 0,897.

Figur 5 The distribution of price elasticities for business class passengers

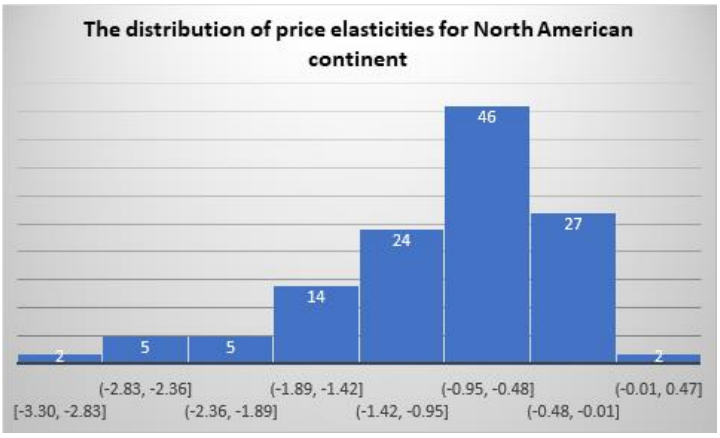
In contrast, observations for the leisure class travelers vary from the most negative reported elasticity –3,54 up to the extremely positive one about 0,77 from the collection of 154 estimates. The majority of price elasticities for the business segment accumulated between the –0,78 and –0,11, while for the leisure segment observations lie between –1,92 and –0,24. Estimations for the aggregated demand are from all types of travelers on the routes (I.e. when authors were not able to separate data for different segments). The collected dataset consists of 224 estimates and the distribution show that in general elasticities resemble the same pattern as in the chart for the leisure class passengers. The most negative estimation is –3,41, the highest positive among eight collected is 0,88, and the majority of the elasticities accumulated between –1,69 and –0,19.



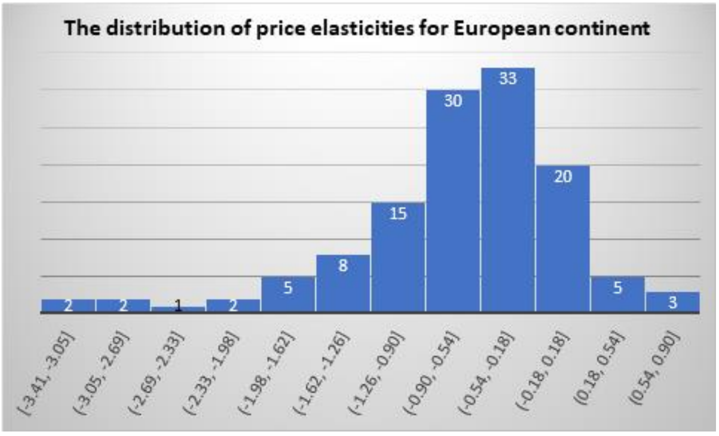
Figur 6The distribution of price elasticities for leisure class passengers

Figur 7The distribution of price elasticities for aggregated class passengers

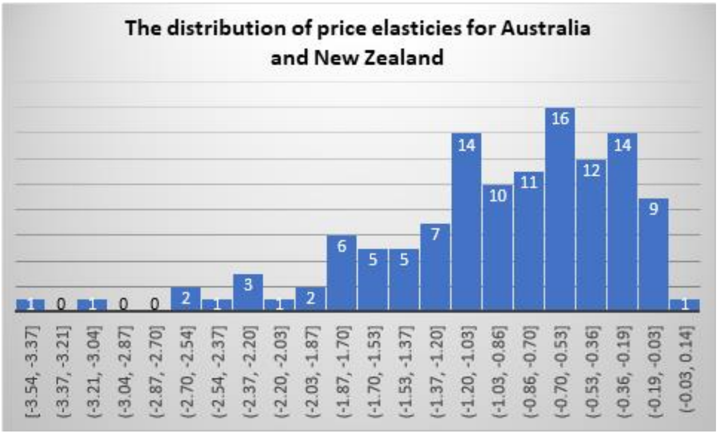
We also created statistical Charts 5-8 for different continents. Conducting a literature review, we noticed that among North American countries the US was the most studied one in the literature, followed by the European countries, Australia and New Zealand. For example, the oldest paper we were able to collect was by Brown and Watkins (1968) on demand for the US market. The dataset included post World War II observations from 1946 to 1966. The oldest Australian paper by Smith and Toms (1978) consisted of observations dated 1964-1977. Thompson's (1974) article about the UK market included data from 1960-1969 and is the oldest paper for the European continent. Studies for other continents are relatively new. Among those we were able to collect only Baikgaki and Daw (2013), Demirsoy (2012) and Hakim and Merkert (2017) obtained large datasets from 1971 till 2015. The rest of the papers for African, Asian, and South American countries are new (datasets are from the year 2000 and on). Those that we were able to find are in the English language, but we expect that some studies, especially older ones, were published in the original or mother-tong and therefore this might be the reason we were not able to find them.



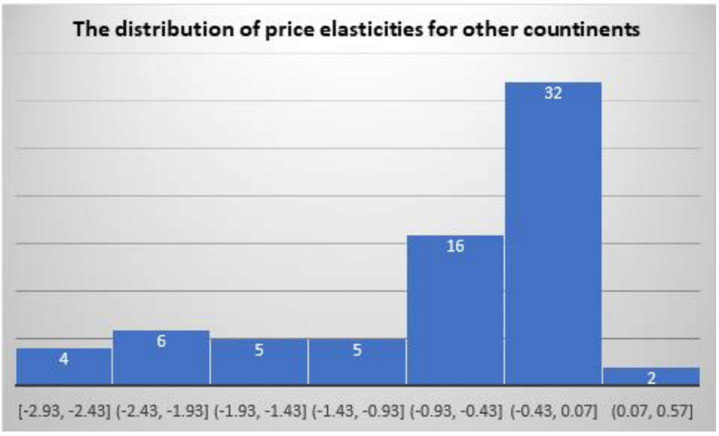
Figur 8The distribution of price elasticities for North American continent



Figur 9 The distribution of price elasticities for European continent

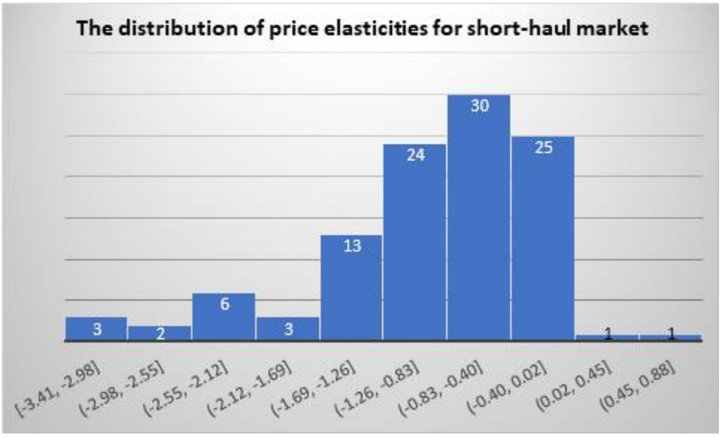


Figur 10 The distribution of price elasticities for Australia and New Zealand

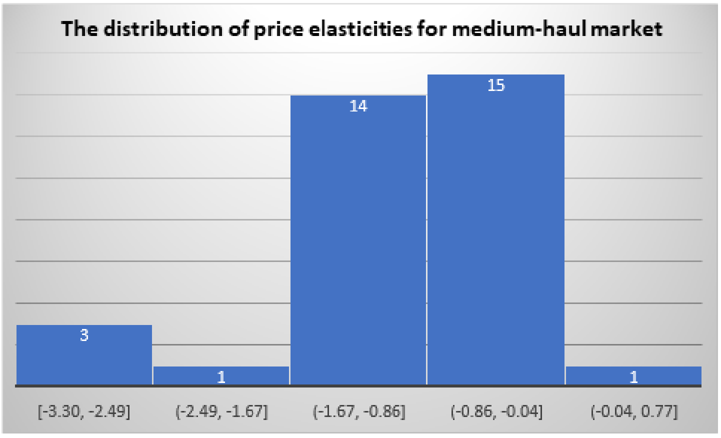


Figur 11The distribution of price elasticities for other continents

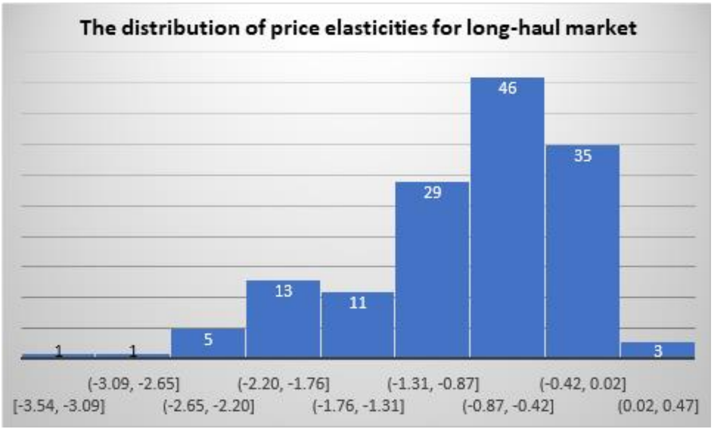
Charts 9-12 for the European and North American countries and Australia and New Zealand show merely the same pattern. The majority of the reported observations are concentrated between -1,9 and -0,19. Most of the positive observations, namely eight, are found in the studies for the European continent. Elasticities for other continents are concentrated between –0,93 and –0,2 and in general pattern shows lower in value estimates representing inelastic demand in these countries.



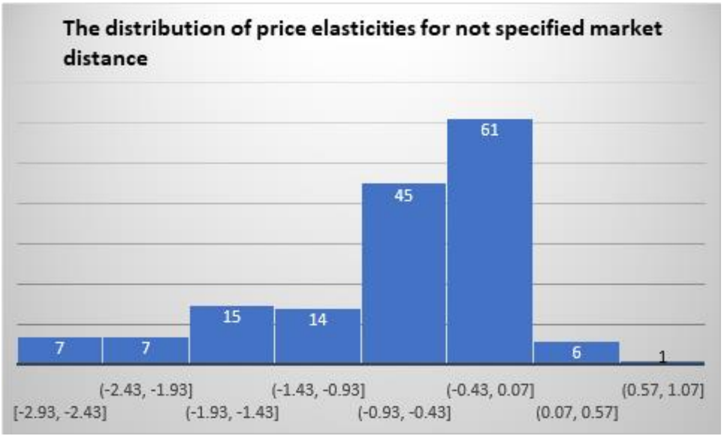
Figur 12The distribution of price elasticities for short-haul market



Figur 13The distribution of price elasticities for medium-haul market



Figur 14The distribution of price elasticities for long-haul market



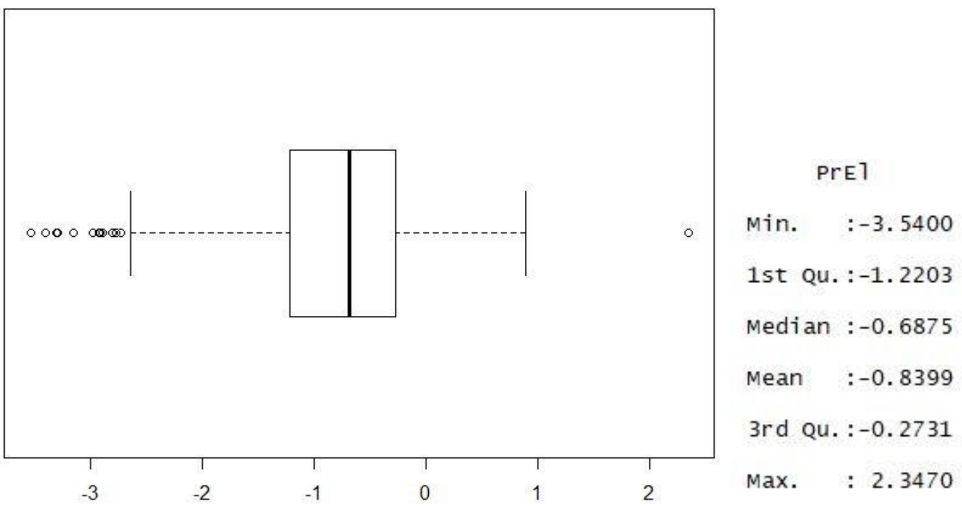
Figur 15The distribution of price elasticities for not specified market distance

The distribution of price elasticities with respect to the market distance, short-haul and medium-haul, shows somewhat the same pattern with the majority of estimations accumulated between –1,69 and -0,2. At the same time reported long-haul market elasticities can be found between the –1,31 and –0,2 with only one extremely negative observation at –3,54 which was found in BOTE (1986) working paper. This significant short-run elasticity represents the Australian domestic long-haul market between 1977-1984. The authors of the BOTE (1986) working paper suggested that the results of their regression show incorrect effects for the non-holiday long-haul markets. In their study, the longer distance was considered - the more negative the price elasticity was obtained.

The distribution of price elasticities for the market where the distance was not specified, or it was not possible to calculate is more spread. Around 106 observations lie between –0,93 and –0,1 representing inelastic demand and four other baskets with a total of 43 observations the range of which is between the –2.93 and –0,9 symbolizing the elastic demand.

For quick interpretation and a better understanding of the overall data distribution, we prepared a box plot to provide a summary of the collected price elasticities with the so-called 5-number summary. The interquartile range shows how the spread is our data and denotes that 50% of the distribution is within the upper and the lower quartiles and the range of estimates is between –0,27 and –1,22. The central tendency of the reported elasticities is –0,69 from the box plot.

The whiskers on both sides of the box plot represent where the remaining 50% of the distribution is, and they are leading to the extrema of the overall distribution of price elasticities which represents the minimum and the maximum range values that are not "unusual" or outliers in the data set. The lowest observation is on the left-hand side –2,5, and the highest one is positive 0.89. It is also seen that our data set is somewhat skewed to the right resulting in the lopsided box plot meaning that on the right section of the box the price elasticities are more condensed. The boxplot also enables to identify possible outliers, which are the values that are greater than 1.5 interquartile ranges away from the upper and lower quartiles. One extreme positive 2,347, found in the paper of Abate (2016), is far right from the box plot and a group of extreme negative (about 12 elasticities in total), the range of which vary between the –3,54 and –2,7, can be seen far left. These outliers represent price elasticities that deviate significantly from other elasticities in the sample and were found in the studies of BOTE (1986), Chi, Koo, and Lim (2010), InterVISTAS (2007), Brown and Watkins (1968), Saad et al. (1983), Straszheim (1978), and Ejem et al. (2017a).

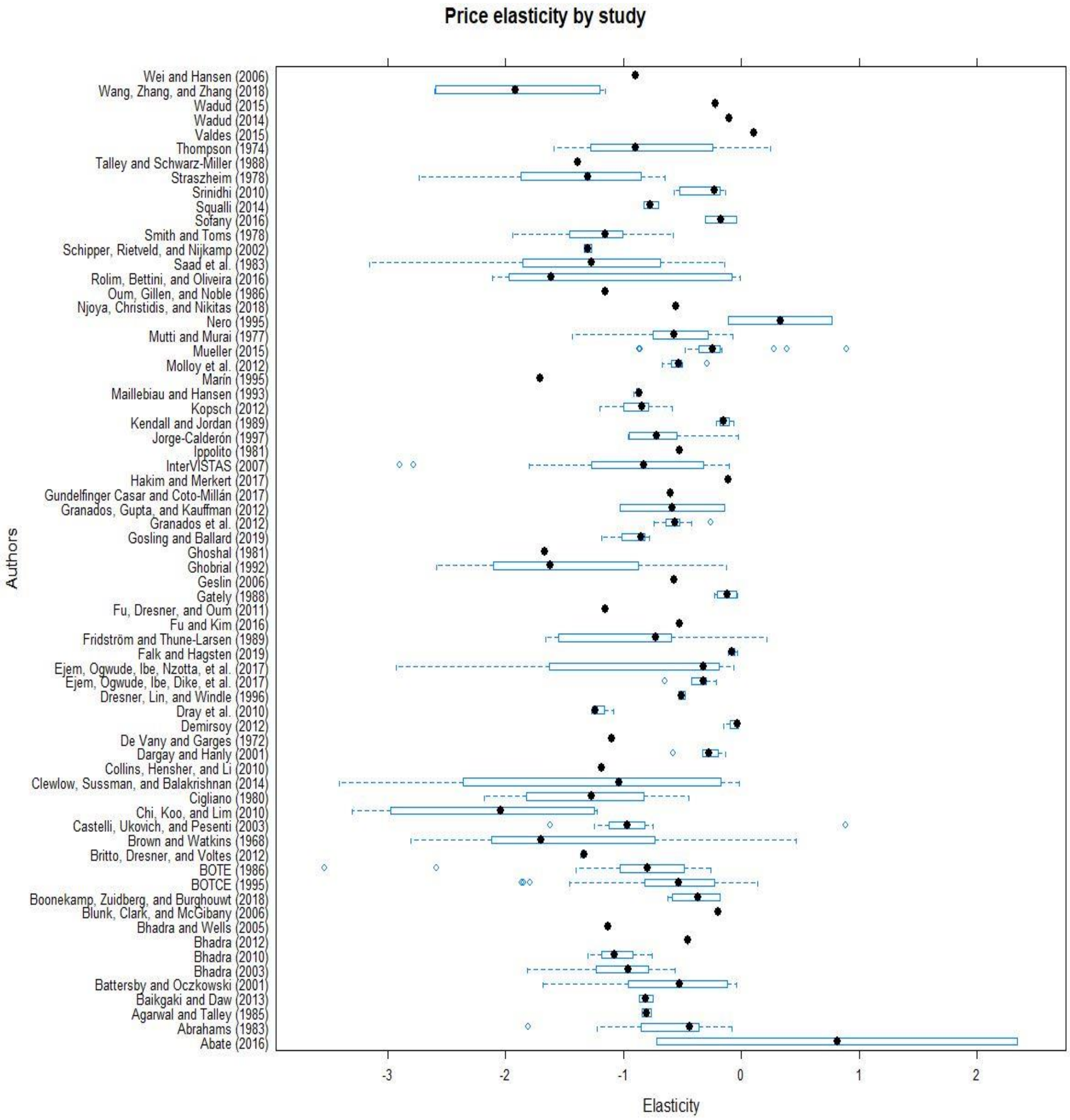


Figur 16 Boxplot of estimated elasticities of output with regard to infrastructure and summary statistics

The vertical axes of the box plot for the individual studies denote the list of the 68 studies presented by the author in alphabetical order and the publication year. The horizontal lines represent the range of elasticities per study. It is seen that the small studies, that reported up to three price elasticities are plotted as the black dots. Studies that report a higher number of estimates are represented by the box plots. Analyzing this box plot, it is seen that there is a presence of heterogeneity across the studies. This can be a result of adopting various data sets, method of estimation, choice of the sample size and explanatory variables, and many more possible study characteristics. This plot also helpful in identifying the outliers that stay aside from the upper and lower quartile of the boxes within the study itself. From the analysis of the box plot that represents the summary of all collected effect sizes, highly negative observations from the papers of, for example, Saad et al. (1983) and Straszheim (1978), are the outliers in the overall sample of the collected elasticities. Whereas they still can be found within the range of the minimum and the maximum values reported by the authors in the study and are non-outliers. Highly negative estimations from the working papers of BOTE (1986) and InterVISTAS (2007) are the outliers even on the individual study level. One highest positive outlier found in the article of Abate (2016) is also a non-outlier in the study itself, but the value significantly deviates from the other reported elasticities in our sample.

It was interesting to look closer at these elasticities to see if they had some similar characteristics that made them stay aside from the other estimates in the sample. The first instinct was to see if the fare class was the reason because we expected that the leisure market was the investigated area. However, that was not the case since only one estimate from BOTE (1986) refers to the leisure market, while the rest reported related to the aggregated passenger market. Concerning the time horizon of the elasticity, the authors reported equally between the short-run, the long-run and time horizon unknown category. The only one respective category, data level aggregation on the route level, combined them all. All these estimates were obtained from the route spesific studies, which can indicate that route level estimates are more negative which is consistent with the theory mentioned earlier by InterVISTAS (2007) and IATA (2008).

The presence of outliers can reflect an important or a special case in the study and merely deleting them from the analysis does not make sense. Instead, we decided to test our model with and without the outliers and to compare the outcome. Obtained results and discussion presented in 2.5

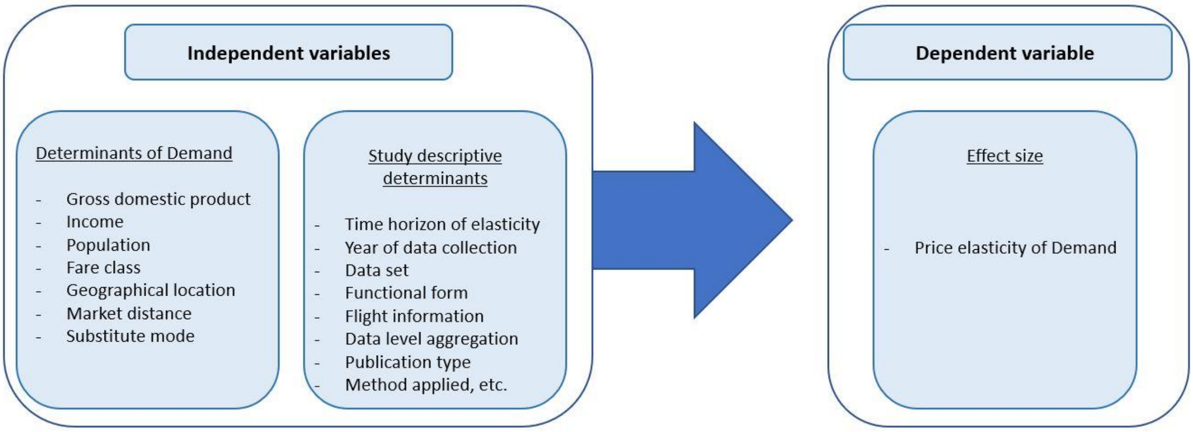


Tabell 4 Source: Author's computation: Boxplot of estimated price elasticity across studies

2.2 Search protocol

From the selected works, we gathered the reported elasticities, their standard errors and t-values, and information on different characteristics in the form of dummy variables. The set of elasticity estimates is the dependent variable, while the variety of the study descriptors serve as the independent variables or explanatory variables that can explain the variance in the dependent variable. It must be noted that we did not distinguish between significant and non-significant variables due to publication selection bias. Variables that reported insignificant estimates were still included and coded 1 for presence even though these are not significantly different from zero.

Figure 19 summarises how the explanatory variables were divided into two main subgroups: the demand determinants and the study descriptive determinants.



Figur 17Dependent and independet variables used

We collected the data from the studies, either directly or indirectly. The direct method means that the studies explicitly provided the information without any additional search or calculations needed from our side. The indirect method indicates that the authors in their work did not directly mention how they obtained the information, but instead left explanations enough in order to figure out the information ourselves. An example of this is that some authors did not mention the distance but rather provided information on the origin and destination endpoints.

2.3 Coding of data

The majority of the variables have been subdivided into different sub-categories where each of the observed estimates can be placed based on the information collected as shown in Appendix B. The table also visualizes variables description, which shows how the different descriptors were coded as dummies except for Year of Data since we want to measure how the change in year affects the price elasticity which is something we cannot do with the use of an assigned dummy. Appendix B provides a summary of the control variables that we coded and further tested in the master thesis.

Most of the data, with respect to determinants of the demand in air transportation, were easily traceable. Whereas the coding of some study descriptive characteristics and understanding how the study was conducted needed more attention. Therefore, below we would like to provide an insight into the coding of some specific variables.

The author-specific variable is closely related to the investigation of the non-independency of the reported elasticities. Excluding the studies that report more than 19 estimates per work will lead to a heavily reduced number of elasticities in the data set and a possible bias. What if these studies, even though they report a large number of elasticities, are in fact, very significant and their results are more precise compared to those that report only one or two estimates. Therefore, instead of exclusion, we decided to assign to such studies their own author specific variable. The list of the authors and the number of elasticities were collected from the study is presented in the table 6

Tabell 5 Number of estimates collected from studies

Study	**Estimates reported**
BOTCE (1995)	40
BOTE (1986)	24
Granados et al. (2012)	22
InterVISTAS (2007)	19
Mueller (2015)	21
Saad et al. (1983)	34

Estimates that originated from a specific study were then grouped into the designated category. For example, estimates that originated from Saad et al. (1983) study were given the value 1 if they originated from this study, while all other estimates were assigned the value of 0. Besides, estimates that did not originate from any of these studies were also given the value of 0 in each category of the author-specific variable.

Time horizon. The categorization whether the price elasticity belongs to the short-run and long-run was usually decided upon the author’s statement. In some cases, the author did not mention it and we had to define ourselves by examining the data and models. By looking at the model, we analysed what type of model was built by the author: static or dynamic (which includes lagged variables). The former model will usually produce short-run elasticity. In the latter case, one can obtain both short-run and long-run estimates. This means that we had to look closer in the model for clues. However, since these types of models are not applicable for the analysis of cross-sectional data, we had to look in the study to see what period of time was analysed in the paper. As mentioned before, Fearnley and Bekken (2005) stated that cross-sectional data usually use annual data, and the estimates can be interpreted as a long-run elasticity. However, not every cross-sectional study uses annual data so that is why we still checked the data collection in each of the cross-sectional studies for information on if the estimated elasticity were short- or long-run. If it was not possible to derive this information or if the author did not present the model in the article, the estimates were placed in the "TimeHorizon_unknown" category.

Geographical location. This category consists of North-America, Europe, Australia/New Zealand and "Other continents". In the beginning, we defined between the US and Canada and collected observations for each country separately. However, we soon realized that there would not be enough studies for Canada. This situation led to the aggregation of both variables into one named "North-America". We also defined between Asia and Africa but again discovered the same problem as described above. This, again, led to the aggregation of Asia, Africa, and South-America into one variable named "Other continents".

Market distance: In our study, we categorized Short-Haul, Medium-Haul, Long-Haul according to their distances. To define between them and to code appropriately, we employed the definition of the markets proposed by Eurocontrol (2005) which states that the distance of the Short-Haul market up to 1500 km, Medium-Haul is between 1500-4000 km and Long-Haul 4000 km and more. We collected the information both ways: directly and indirectly. Directly was when the author gave the information in the original study: distance in kilometers or miles (which we further transformed to kilometers), or stated what market type concerning the distance was studied. Indirectly, when the author gave information about the airports used but not the distance category they belonged. In that case, we used a webpage called "Great Circle Mapper" https://www.greatcirclemapper.net) to calculate the distance between the provided endpoints ourselves. Elasticities collected from the studies that did not provide information on distance or where it was not possible to define what market distance can be applied were coded into the Distance_Unknown category.

Data level aggregation: Here, we distinguish between four categories: National_Level, Route_Level, Above, and Below. If authors had data on the total proportion of passengers transported to and from the country/region in question in period t it was coded as national level, if it was route-specific information on the number of passengers transported between two cities, airports or two predetermined countries we attributed elasticity to the route level data aggregation. In addition, we added two more variables that specified whether the data included an international connection (i.e., Above) or only flights within the same country or continent (i.e, Below).

Publication type: We defined between published and non-published studies. Distinguish between these two was done by looking at the information on the first page. If it belonged to a Journal, it was coded as peer-reviewed. If it did not belong to a journal, it was coded as a non-peer reviewed study. Occasionally it was hard to differentiate between these two, so we used a Norwegian website called “NSD - Norwegian Centre for Research Data” (https://www.nsd.no) where we entered the name of the study, and the website provided information whether the study was published in any journal and whether the journal itself was peered.

Year of data collection: This was coded as a continuous variable and was based upon what year of the dataset was used in the study. If the author collected, for example, data from 1980 to 1990, then we would register the mean year of this data set, which would be 1985. However, if the dataset consisted of years 1970 to 1979, we rounded up the mean year to 1975.

Functional form: We initially started to code a category for the functional form where we defined between double-log and three other types of functional form. The purpose of this was to see if there was a difference in the elasticity reported that used a Log or other functional form. At the end of the data coding period, we noticed that only 10 estimates were obtained using other functional forms which gives too little observations to compare to log-linear 433 estimates. Thus, we further decided to drop these two variables.

Stationarity: if time series data analysis was performed in the study, we expected the authors to address stationarity issues. They either stated that the data was treated for "stationarity", or they mentioned two possible ways of dealing with the problem. One way to deal with this issue by the “first differencing” (first difference of a process or the series of changes that occur in variable Y over the time can be expressed by the formula delta Yt

= Yt - Yt-1. The value of the dependent variable Y observed in a specific period of time t is denoted as Yt and Yt-t represent the same value of Y but in a previous time period Mueller (2015)). Another is – “co-integration” (when a set of non-stationary variables "...share the same common trends, which cancel each other out through a linear combination of the variables" Bjørnland and Thorsrud (2014), Mueller (2015)). If nothing from above was discussed or mentioned, we considered that the data was not treated at all.

Endogeneity. We read the explanations of the authors and searched for any mentioning of endogeneity. Endogeneity can be controlled with the help of instrumental variables (IV) that authors used in their models to limit the unexpected correlation between the variables and the error term or the deal with the reverse causality. Therefore, papers that included IV were considered as those that applied the treatment, and vice versa.

2.4 Meta-regression

2.4.1 Conceptual model structure

The overview of the determinants of the demand for air travel and characteristics of the studies presented in Chapter 1.8.1 of master thesis enable to estimate a general model for this meta-study (van den Bergh et al. 1997, Holmgren 2007):

$$Y = f(X, R, T, L) + e,$$

where Y is the elasticity output and is a dependent variable, X represents a set of independent variables that have an effect on the explained variable, T is the time period in which the studies were conducted, L denotes the geographical scope of the study and R serves as the control variable that characterizes applied methodology in the study to obtain Y. The variables in the model were further transformed into the logarithmic form so that the resulting coefficients from the regression can be interpreted as the elasticities of the dependent variable with respect to the set of independent variables.

2.4.2 Aggregated Model: Building and estimation

After finishing the coding of the data, we wanted to check the relationship between the dependent and the set of independent variables describing study characteristics and the demand determinants. Therefore, we started the analysis with the creation of Pearson’s correlation matrix, which can be found in Appendix 1.

From this matrix, we have discovered that some variables are perfectly correlated between each other. The dark blue squares indicate the perfect negative correlation of –1, while the red squares mean the perfect positive correlation of 1. The less colored squares indicate moderate correlation, and the white squares stipulate that there is no correlation. A matrix is a useful tool for understanding how the different variables react to each other. The variables that experience perfect correlation are Domestic and International, Above and Below, Route_Level and National_Level, Peer_reviewed and Non-peer-reviewed, OLS, and Method_Other meaning that one of the two regressors should be included into the base case in order for the regression to work.

Another thing one can notice from the matrix is that Above and International, Below and Domestic are perfectly and positively correlated. Analyzing the excel table led to the conclusion that these variables meant the same thing. While coding, we were interested in what type of flights were considered, and then also checked what data type the authors used in the study. Thus, if for example, the author considered International flights in the study, then on the data level aggregation the same was reflected by the Above variable. Because they are highly associated with each other, we decided to drop International and Domestic variables from our model, which can bias the result and reduce the explanatory power of the model. In addition, Cross-sectional and Long-run is correlated to each other since cross-sectional method yields Long- run elasticity which has been explained earlier.

The remaining variables show moderate, low, or no correlation, which is not a problem when constructing a regression model.

The next step was to deal with the estimates, which value significantly deviate from other elasticities in the sample. The reason is that outliers might influence the magnitude of the effect size we were going to obtain. After close examination and discussion, we decided not to exclude the most negative elasticities discussed closely in

Section 6.2 of this master thesis. The reason for this decision is that they originated from different papers, data sets, estimation methods, and considered different markets. The only thing they had in common was the *Route_Level* data aggregation, but since this is consistent with the theory, it did not raise any concern for further analysis.

The next estimate that caught our attention was the highest positive 2,347 that originated from the work of Abate (2016). The leap between the highest positive non-outlier elasticity 0,897 and this extreme one is too large. Abate (2016) reported another estimate of –0,719, which is closer to what is typically estimated by other studies, which made us question why such a result was obtained. After a closer examination of the study, it was neither possible to find out the reason for this, not it was explained by the author himself which made us question the validity of this particular estimate even though it was significant in the study. Leverage plots were applied in order to identify the problem, but it showed no significantly results which lead to our next option. A regression was run multiple times with and without this positive estimate. We noticed that its inclusion impacted the intercept on average by 0,08, implying that a 10% increase in prices will result in an almost 1% change in the quantity demanded. The adjusted R2 also resulted in poor value, meaning that the explanatory power of the regressors decreases. After this small examination, we decided to exclude this estimate from the data set. The total number of estimates resulted in 443 observations. Large model can be viewed in figure 18.

We started the analysis by creating the base case of the large model. The properties of it are summarised in Table 6:

Tabell 6 The base case summarry of the large aggregated model

Aspect	**Properties of the base case**
Type of the data	*Fare* *North-America* *National_Level* *Below* *Pooled* *Quaterly* *Stationarity_untreated* *Endogeneity_untreated*
Passenger class	*Aggregated*

Time horizon of elasticity	*TimeHorizon_unknown*
Market distance	*Distance_Unknown*
Publication type	*Non-peer-reviewed*
Estimation method	*Method_Other*

The process of identifying the best possible model started with a large one where 27 other variables specified in Table 7 were included together with the author specific dummies. The value of the intercept should be interpreted as the expected elasticity when all other variables in the model are held constant (i.e., they are equal to zero). The *Intercept* had the correct negative sign according to the theoretical standpoint and among other factors could be interpreted as the price elasticity estimate of the demand for the domestic air travel originated from the aggregated class of passengers on the North American continent. While the obtained intercept was significant, many of the explanatory variables in the model were not significant at the 5% level, which built the foundation for the process of elimination. However, we had to be careful when eliminating because according to Wooldridge (2014) omitting relevant control variables would result in the underspecifying of the model and biased estimators.

The adjusted R2 gave an idea of the explanatory power of the model. During the elimination process, the goal was to obtain an adjusted R2 value as high as possible, meaning that while eliminating the irrelevant variables, the explanatory power of the model was not compromised. Through the whole elimination process, a close eye was kept on the intercept, and explanatory variables coefficients, standard errors, significance level, and the model's adjusted R2. After several hundred model constructions, we decided to present the best of them next.

```
Residuals:
     Min       1Q   Median       3Q      Max
-2.59562 -0.29103  0.05852  0.38076  2.06413

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              -0.690216   0.291177  -2.370 0.018230
`BOTCE (1995)`            0.295324   0.315222   0.937 0.349374
`BOTE (1986)`            -0.492117   0.287094  -1.714 0.087263
`Granados et.al (2012)`  -0.087724   0.281182  -0.312 0.755213
`InterVISTAS (2007)`     -1.378688   0.376805  -3.659 0.000286
`Mueller (2015)`         -0.892481   0.338900  -2.633 0.008772
`Saad et.al (1983)`      -0.645770   0.223218  -2.893 0.004020
`Airfare Sub.`           -0.244926   0.138365  -1.770 0.077447
GDP                      -0.056925   0.113771  -0.500 0.617101
POP                      -0.071247   0.106301  -0.670 0.503087
Frequency                 0.254404   0.131255   1.938 0.053281
Sub_Mode                  0.235712   0.144825   1.628 0.104387
Business                  0.287998   0.153410   1.877 0.061186
Leisure                  -0.104013   0.124357  -0.836 0.403413
`Short-run`               0.161428   0.221457   0.729 0.466457
`Long-run`               -0.359669   0.245647  -1.464 0.143917
Europe                    0.232577   0.155526   1.495 0.135575
`Australia/NZ`           -0.254007   0.196234  -1.294 0.196255
`Other continents`        0.452100   0.169866   2.662 0.008085
`Short-Haul`             -0.056835   0.139499  -0.407 0.683911
`Medium-Haul`            -0.074135   0.187633  -0.395 0.692969
`Long-Haul`              -0.417270   0.165791  -2.517 0.012223
Route_Level              -0.273527   0.114005  -2.399 0.016875
Above                     0.328593   0.123967   2.651 0.008346
Peer_reviewed            -0.418244   0.196146  -2.132 0.033576
`Year of Data`            0.005795   0.005712   1.014 0.310973
Monthly                  -0.325477   0.171507  -1.898 0.058433
Annual                   -0.312503   0.171685  -1.820 0.069458
`Time-series`             0.343754   0.186833   1.840 0.066507
`Cross-sectional`         0.661174   0.248305   2.663 0.008056
Panel                    -0.248863   0.180473  -1.379 0.168664
OLS                       0.257461   0.113318   2.272 0.023603
Stationarity_reported     0.125375   0.139100   0.901 0.367945
Endogeneity_reported      0.025861   0.124387   0.208 0.835403
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6563 on 409 degrees of freedom
Multiple R-squared:  0.2627,    Adjusted R-squared:  0.2033
F-statistic: 4.417 on 33 and 409 DF,  p-value: 2.496e-13
```

Figur 18 Large model output

```
Residuals:
     Min       1Q   Median       3Q      Max
-2.56847 -0.34068  0.04059  0.45442  1.89239

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          -0.758707   0.166843  -4.547 7.07e-06 ***
`Saad et.al (1983)`  -0.462591   0.162589  -2.845 0.004651 **
StEr_reported        -0.326169   0.110644  -2.948 0.003373 **
Frequency             0.351183   0.114266   3.073 0.002251 **
Business              0.480662   0.110313   4.357 1.65e-05 ***
`Long-run`           -0.514274   0.133329  -3.857 0.000132 ***
Route_Level          -0.404181   0.075439  -5.358 1.38e-07 ***
`Year of Data`        0.013634   0.003302   4.129 4.38e-05 ***
`Time-series`         0.313008   0.120761   2.592 0.009867 **
Panel                -0.132156   0.134209  -0.985 0.325323
`Cross-sectional`     0.724435   0.197658   3.665 0.000278 ***
Endogeneity_reported -0.108739   0.078387  -1.387 0.166094
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6658 on 431 degrees of freedom
Multiple R-squared:  0.2004,    Adjusted R-squared:   0.18
F-statistic: 9.818 on 11 and 431 DF,  p-value: 5.935e-16
```

Figur 19 Optimal aggregated model

The properties of the resulted base case of the best aggregated model are presented in Table 7:

Tabell 7 The base case summary of the best aggregated model

Aspect	**Properties of the base case**
Type of the data	*Estimates that do not originate from Saad.et.al (1983)* *Standard errors not reported* *Frequency not considered* *North-America, Europe, Other continents* *National_Level* *Pooled* *Endogeneity_untreated*
Passenger class	*Aggregated, Leisure*
Time horizon of elasticity	*TimeHorizon_unknown, Short-run*

In the majority of the regression outputs, the Australia/NZ control variable proved to be insignificant. Meanwhile, the estimate of the dummy variable, assigned for Saad et al. (1983) (the author reported 37 elasticities), is -0,463 at a significance level of 0,001. The main issue with this author-specific variable is that the authors studied the demand on air transportation for Australia and New Zealand, and we noticed under several regressions that Saad's variable that this author dummy in a way reflects Australia/NZ market. Thus, we considered that Australian and New Zealand's market would be represented by Saad et al. (1983) paper.

Figure 19 shows the results of the regression. The coefficient of base price elasticity is –0,759 corresponds to what other studies typically report. The intercept is highly significant and has the correct sign. Among other variables characteristics, this short-run elasticity estimate obtained from the pooled data set interprets the demand originated from the aggregated and leisure passengers. According to this base case, elasticity is applicable for all continents.

Studies that provide standard error for the estimate tend to report more negative estimates by –0,326. Studies, where the Frequency variable was added in the model, report less negative elasticity. The coefficient is 0.351 and highly significant at 0,01 level. The Business variable reports the expected prefix and reasonable estimate according to theory. Usually, studies that examine the Business segment report less negative elasticity compared to the Leisure and Aggregated market segments. This variable is highly significant at a 0,0001 level with an estimate of 0,481. The Long-run variable estimate has value -0.514 and shows expected prefix according to theory, meaning that studies that report long-run elasticities are more negative when compared to the short-run time horizon.

The data level aggregation estimates are of expected prefix according to theory. Studies that considered Route_Level data aggregation reported more price sensitive elasticity compared to the studies that used National_Level data aggregation. The obtained coefficient -0,404 is highly significant at 0,0001 level. Year of Data variable reports an estimate of 0,012 and is highly significant at 0,0001 level. It indicates that the newer studies that use more recent data sets provide less negative price elasticities suggesting that passengers became less sensitive to the prices with the time.

Data type also seems to influence the estimated elasticity. If a Time-series analysis was conducted, the authors tend to report less negative elasticity by 0.313. Also, with the Cross-sectional data analysis, the reported elasticities will be less negative. Both variables have a significance level of 0,0001. The Panel data variable has a coefficient of –0,132 but is not significantly different from zero at the 5% level. Endogeneity_reported has a more negative estimate of –0,109 but is also not significantly different from zero at the 5% level.

2.4.2.1 Test diagnostics

The value of the adjusted R2 did not deviate too far from the value obtained in the large model, which means that we were able to identify the majority of the variables that had the explanatory power in the model. However, there were still some variables that we thought might increase the explanatory power of the model. All the variables that were in the base case were then reintroduced one by one in order to identify any variables that had a more substantial impact on the explanatory power of the model. In the end, we did not succeed because all the base case variables had a minor effect, which means the 0,0253 = 2,5% of the explanatory power was made up by all the variables in the base case. The overall adjusted R2 for the model is 0,18, which means that the model does not explain 82% of the variation in price elasticity. However, we are not able to benchmark this model's fit with any other in the field since there is none available. This means that we could not justify if this is a good model or not.

In order to check the model for homoscedasticity assumption, the Breusch-Pagan test was applied. The test assumes that the variance of the residuals is constant at P > 0,05 in H0. According to the test results presented in Appendix 3 the P-value is 0,00002 meaning that the H0 can be rejected and accept the H1 where the variance is not constant. According to the residuals vs. fitted plot, there is a particular pattern of a "fish shape". Besides, a red line informs whether heteroscedasticity is present or not. A flat red line indicates that the residuals have a linear pattern. However, from residuals vs fitted plot in appendix 3 it can be seen, that the line is not flat, but instead starts to bend downward suggesting the presence of heteroscedasticity.

The Normal Q-Q plot (quantile-quantile) plot, provided in Appendix 3, proves that the residuals are normally distributed. All the residuals are not perfectly lined, but the overall picture suggests that there is not much skewness in the data. The last step in this analysis is to investigate if there are any influential points, and this can be done with the help of residuals vs. leverage plot. According to residuals vs fitted plot in appendix 3, there are no influential points reported, meaning that none of the estimates influence the model.

In order to account for heteroscedasticity presence, White's test was then applied in order to produce corrected standard errors. The output can be viewed in figure 22. Now the results can be interpreted even when the heteroscedasticity is present.

2.4.3 Leisure Model: Building and estimation

Having a sufficient sample size, we were are also interested in building the model specifically for the leisure market segment to see if the results would differ from the output reported from the aggregated model. It is worth mentioning that InterVISTAS (2007), Airfair Sub., Panel, and the Above variables were removed due to no observations reported/coded for the leisure class of passengers in these categories in Excel. A new correlation matrix, presented in Appendix 4, was constructed for the 154 leisure estimates. It uncovers somewhat the same correlation between variables as in the aggregated model. Thus, we will not discuss the correlation matrix again. Once again, we proceeded with the building of a large model where a regression was run with the inclusion of the majority of regressors. The intercept resulted in a highly positive but insignificant coefficient of 2.97 in the over-specified model.

The first model presented used same predictors used in the aggregated mode, showing that this model was not the optimal fit for leisure market. The intercept of -0,547 had a correct sign and was significant at the 10% level. Nonetheless, the adjusted R2 value was reduced to 0,208 while the large model displays an adjusted R2 of 0,374, meaning that this model loses 17% of its protentional explanatory power. For this reason, we rejected this model and decided to test more of them to see if it was possible to construct a model with better explanatory power.

Tabell 8 Base case for leisure

Aspect	**Properties of the base case**
Type of the data	*Estimates that do not originate from Saad.et.al (1983)* *Standard errors not reported, Frequency not reported* *North-America*, Europe, Other continents *National_Level* *Pooled* *Endogeneity_untreated*
Time horizon of elasticity	*Short-run*
Market distance	*Distance_Unknown*

A final and best model for leisure segment presented in a 21

Results for leisure model

	Dependent variable: Price Elasticity
Constant	-1.081***
	(0.197)
Long-run	-0.466**
	(0.205)
Europe	0.554***
	(0.122)
Cross-sectional	0.808***
	(0.277)
Time-series	0.359***
	(0.113)
Year of Data	0.018***
	(0.007)
Stationarity reported	-0.436**
	(0.193)
StEr reported	-0.482***
	(0.184)
Observations	154
R2	0.278
Adjusted R2	0.243
Residual Std. Error	0.568 (df = 146)
F Statistic	8.033*** (df = 7; 146)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figur 20Optimal leisure model

Tabell 9 Base case summary for optimal leisure model

Aspect	**Properties of the base case**
Type of the data	*Standard errors not reported* *North-America*, Australia/NZ, Other continents *Pooled, Panel* *Stationarity_untreated*
Time horizon of elasticity	*Short-run*

The intercept of the final leisure model resulted in a value of -1,08 and is highly significant. This short-run estimate can be interpreted as the elasticity of demand for all studied continents except European that originated from the pooled and panel data analysis. In this model, the Europe variable proved to be significant, which provides an insight into the continent-specific adjustor compared to the base case. The price elasticity adjustor for the European continent is 0,554, meaning that the leisure class tends to be less sensitive to prices compared to the North-America continent, Australia/NZ and other continents.

The Long-run variable reports an expected negative coefficient of –0,466, which is consistent with the theory suggesting that the long-run price elasticities are more negative compared to the short-run estimates. Studies that used cross-sectional and time-series data type report negative estimates compared to studies that implement panel or pooled. Concerning the year of the data set, more recent studies report less negative estimates suggesting that with passengers became less sensitive to the prices over time. If the authors treated their data for stationarity, then elasticities from such studies resulted in more negative estimates. Studies that reported standard errors also tend to report more negative estimates compared to the ones that did not.

2.4.3.1 Test diagnostics

The adjusted R2 value is 0.243. When comparing this one to the large model, one can see that the model's explanatory power is reduced by 0,166, meaning that some predictors might be missing. However, this was the best model produced among the others, with the best explanatory power, reasonable intercept, and significant control variables.

The Breusch-Pagan test, showed a P-value of 0.758, meaning that in this case, H0 can be accepted at P > 0,05. This further implies that heteroscedasticity is not present in the model Appendix 7 The Normal Q-Q plot displays relatively normally distributed data where the majority lies on the diagonal line. The residuals vs. leverage plot visualized on shows that there are no specific points that fall outside Cook's distance, meaning that there are no influential points that need to be dealt with. Regression output with robust standard errors can be viewed under.

Results Aggregated model with heteroscedasticity-robust standard errors

	Dependent variable: Price Elasticity
Constant	-0.759***
	(0.146)
Saad et.al (1983)	-0.463***
	(0.150)
StEr reported	-0.326***
	(0.105)
Frequency	0.351***
	(0.123)
Business	0.481***
	(0.064)
Long-run	-0.514***
	(0.135)
Route Level	-0.404***
	(0.082)
Year of Data	0.014***
	(0.003)
Time-series	0.313***
	(0.092)
Panel	-0.132
	(0.137)
Cross-sectional	0.724***
	(0.190)
Endogeneity reported	-0.109
	(0.087)
Observations	443
R2	0.200
Adjusted R2	0.180
Residual Std. Error	0.666 (df = 431)
F Statistic	9.818*** (df = 11; 431)
Note:	*p<0.1; **p<0.05; ***p<0.01

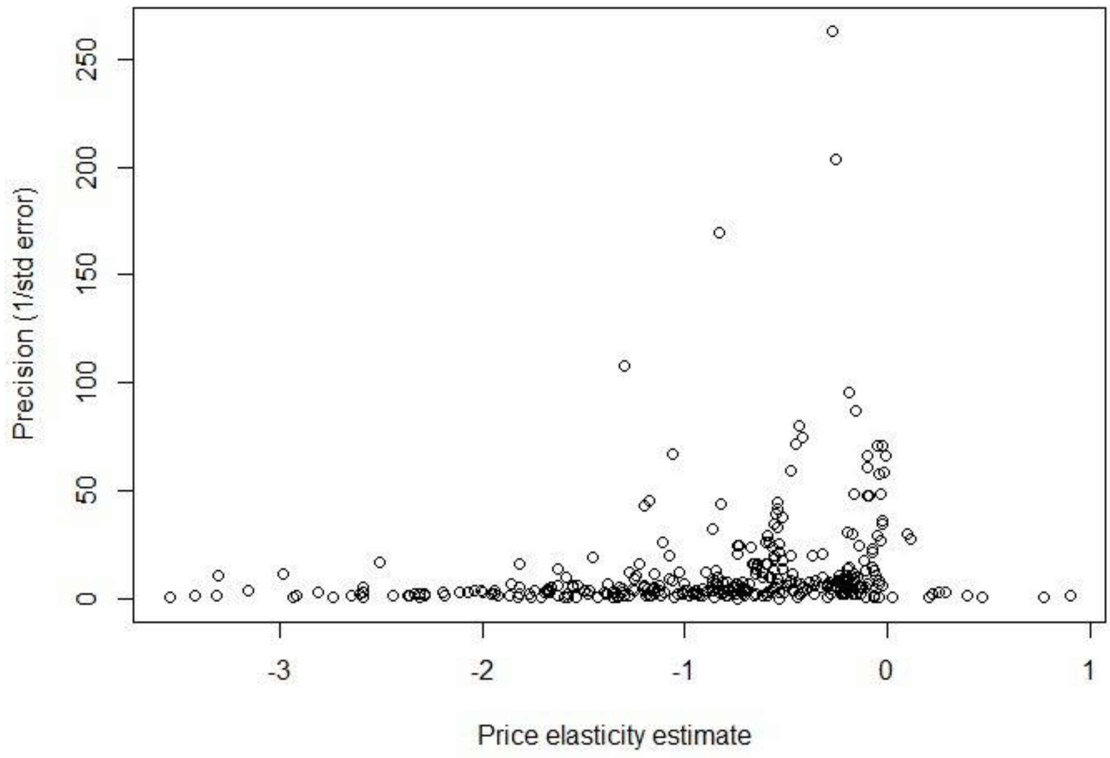
Figur 21Robust standard errors

2.4.4 Business Model: Building and estimation

The purpose of constructing a business model was to investigate what variables are important and how they affect the price elasticity when the business traveller segment was explored separately. We wanted to investigate if there was no significant change in variables used or it the estimate differed from that one that can be calculated from the aggregated model with the help of the adjuster. However, since the set of the collected articles reported only 45 elasticities, we knew that this could pose a challenge in the estimation. The reason is that several variables in the model did not meet the expectation of 10 observations per explanatory variable. The variables that did not report more than 10 observations were: Frequency, Substitute mode, POP, Europe, Domestic, Short-Haul, Medium-Haul, Pooled, Panel, Endogeneity reported, and Stationarity reported. With this in mind, we tried to construct a model with the rest of the available variables that exceeded 10 observations. Several different combinations were explored, but we were unable to produce a business model with a reasonable intercept and significant variables. Most of our models resulted in an insignificant intercept, and the ones that were significant produced an unreasonable base case elasticity that was higher than the aggregated or leisure model. In the end, we concluded that our dataset for business market was not adequate.

2.4.5 Publication bias

Publication bias occurs when researchers favor a particular type of estimates compared to others, thus resulting in the study being unrepresentative of the population in the area and can mislead the reader to think that the effect size is more significant than what truly is (Rothstein, 2008). Figure 23 presents the inverse funnel plot that shows to what degree the publication bias exists in the collected data set. On the vertical axis, the inverse of the standard error values, or precision, are plotted, and the horizontal axis displays the price elasticity observations from the studies.

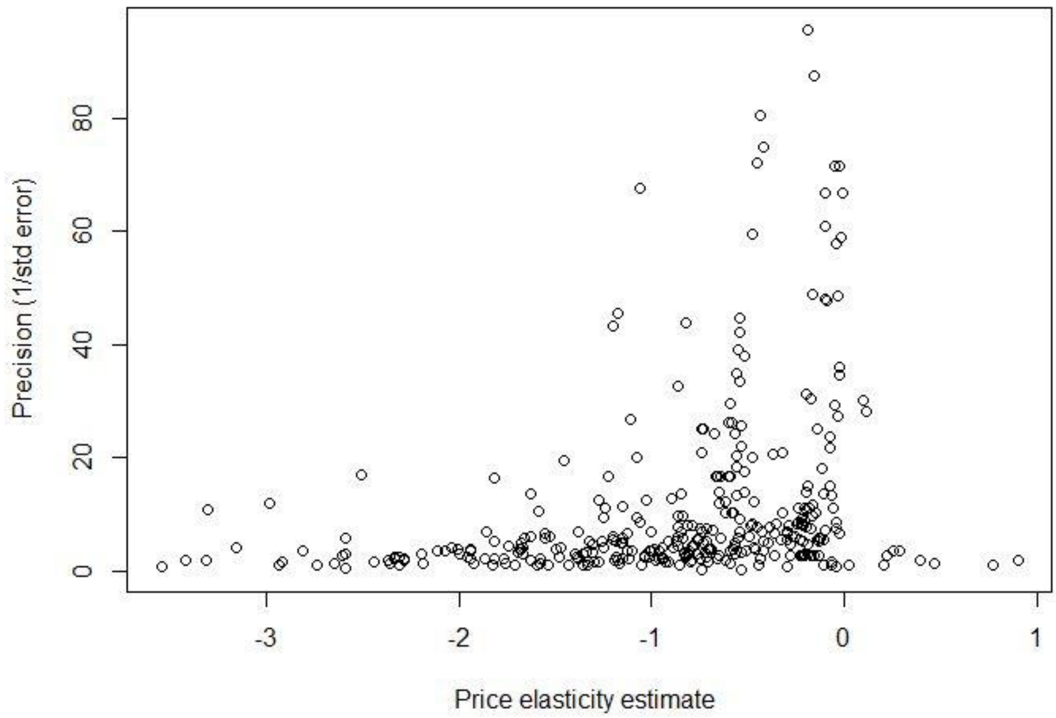


Figur 22Funnel plot

Since the standard error values were compulsory for the creation of this plot, the sample size was reduced to 352 observations because not all authors reported standard errors together with the elasticities. Even though we included both significant results and not from the collected set studies, we were still not able to eliminate publication bias, which can be explained in several ways. Figure 23 shows that the funnel plot is asymmetric towards the negative side, implying that researchers clearly prefer to report mostly negative results compared to positives ones. This is probably a result of theoretical expectations existing in the scientific field. Moreover, positive results imply that, for example, a 10% increase in airfare will lead to a 1% increase in demand, which is considered contradicting and therefore, not many authors report them. However, if published, these estimates were usually reported in the preliminary estimation stage where different types of models and methods were tested, and the majority of the estimates were insignificant.

For example, Brown and Watkins (1968) reported positive estimates, two of them to be exact, even though this is a published article. Both estimates were for the Long-Haul market with the values of 0,466 and 0,024 and with no explanation of how these were obtained. However, the standard errors for both estimates were quite high of 0,766 for the first estimate, and 0,922 for the last estimate meaning that the data is not representative and elasticities are insignificant. Valdes (2015) in his work reported positive estimates which were based on the price of the jet fuel as a proxy for airfare. The author later stated that the reason for the poor quality of elasticities arose due to the non-availability of the real airfare data.

In the funnel plot, four points that stood out from the rest of the reported estimates can be noticed. One elasticity originates from Granados et al. (2016), while the other three come from InterVISTAS (2007) working paper. These studies reported extremely low standard errors that range from 0,0038 to 0,0092, meaning they used large samples, which resulted in greater accuracy of the calculated elasticities. Another thing that caught our attention is that some observations were grouped into two "columns". In order to examine closer this issue, the four high precision estimates were removed from the plot (Figure 24). After a closer examination, it was discovered that estimates that ranged from –0,4 to –0,6 with the higher precision originated from Granados et al. (2016). The authors reported several estimates that had a very low standard errors, which resulted in this particular pattern. From the funnel plot, one can see that estimates from-3,6 to –0,8 and positive estimate of +0,05 and upwards, report lower precision, meaning that these estimates are not precise. Seem like estimates that ranges from 0 to –0,8 are the ones who are more precise. Policy makers should be careful when using macro estimates for basis when deciding on future changes in prices.



Figur 23Funnel plot

One reason why the funnel plot is asymmetric might be that when the authors find positive results, they could be reluctant to publish them since it goes against the expected theory. In the case when they want to publish their results, they might find it hard to get such studies approved by reviewers since the results are unappealing to the public. Another reason is that the majority of the "file drawer" studies are still not discovered, meaning that there might be many more studies out there reporting positive outputs that could make the funnel plot more symmetric. However, due to the time constraint, we were not able to spend time more on tracking down "file drawer" studies.

2.5 Discussion

The aggregated models display a low adjusted R2 meaning that the explanatory power is low, which can be reflected by a more substantial variance between the studies. The sub-analysis of the leisure market can confirm this suspicion with the help of the leisure model's higher adjusted R2. The reason for this is that the leisure model is disaggregated from business and aggregated travellers. Meaning studies that investigate the leisure market have more characteristics in common. The leisure model can explain better the variance, thus reducing heterogeneity. However, the aggregated model is not able to do this because all the information is put into on model, meaning that the studies have a higher variance in the data set.

Answering the RQ 1, it can be stated that the intercept of -0,76 obtained from the aggregated model presented in the figure 22 can be considered as the base price elasticity. According to the base case, this short-run elasticity estimate that is obtained from the pooled data set interprets the demand originated from both aggregated and leisure passengers.

Answering the RQ 2, the abowe mentioned elasticity is applicable for all continents except the Australian and the New Zealand markets. The respective elasticity for the latter two markets is -1,22 which is obtained by the summation of the base price elasticity and the respective adjuster (i.e., coefficient of the Saad et al. (1983) variable). This new value suggests that in the short-run the leisure and aggregated classes of passengers are more price sensitive compared to the North-American, European, and other continents resulting in the elastic demand for air transportation. Our estimates are slightly lower compared to the average elasticities for leisure class reported in the work of Gillen, Morrison, and Stewart (2003). The authors denote that on the short-haul market median price elasticity is -1,520, on the domestic long-haul market elasticity is equal to -1,1, and on the international long-haul markets it is -1,04.

Elasticity for the business class passengers can be obtained by summing the intercept and the coefficient of the business variable. The new value is -0,28 and can be interpreted as the short-run elasticity of demand for business class travelers applicable for all continents except the Australian and the New Zealand markets. The average short-run airfare elasticity for the business class segment in Australia and New Zealand will be equal to -0,48. These estimated price elasticities do not deviate much from the estimates reported in the work of Gillen, Morrison, and Stewart (2003). Their results suggest that estimates for business class on the short-haul-market is -0,7, and on the long-haul market vary from –1,15 for the domestic routes to -0,27 for international routes.

The values obtained for two markets with respect to the purpose of air travel are consistent with the theory implying that business class travelers are less sensitive to price compared to leisure passengers (BOTCE 1995; Oum, Waters, and Yong 1990). Most of the business-related trips are being paid by the firms and not by the employees themselves. This class of passengers is more willingly pay for extra services such as last-minute booking, faster check-in, access to lounges, and priority in boarding. In contrast, leisure class passengers, being more budget constrained, prefer early booking of the tickets which, in general, are lower compared to the price of the ticket closer to the date of the departure. They are more flexible in their plans and less time-sensitive, meaning that the trip easily can be postponed for later dates or even canceled if the airfares are too high in a given time period.

Long-run adjuster enables to derive long-run elasticity estimate of the demand originated from both aggregated and leisure passengers. The value of it is -1,27 and is applicable for all discussed continents except the Australian and the New Zealand markets. For these two latter markets, the summation of the coefficients will result in the long-run elasticity of -1,73. The long-run price elasticities are more negative compared to the short-run estimates when comparing their magnitude based on the time horizon, which is also consistent with the economic theory. The theory states that in the short-run time horizon, consumers will not have time to adjust to price changes, and most of them will still prefer to travel. While long-run estimates reflect that consumers can adjust better by considering the possibility to shift to other modes of transportation, or even relocate to reduce the number of trips by air significantly (Brons et al. 2002; Doganis 2010).

Despite we failed to obtain adjusters for any markets with respect for their distance (i.e., short-haul, medium-haul and long haul) the two above mentioned base price elasticities and their adjusters can be used to explain the demand for the respective markets with one suggestion. The best case scenario will be obtained with the summation of base price elasticity with one of the adjusters. Inclusion of two adjusters should be interpreted cautiously guiding the researcher in the possible outcome of the model and the magnitude of the elasticity.

Answering the RQ 3, we can say that studies that used route-level data aggregation reported estimates that are more negative in magnitude, which confirms the theory that on the national level, passengers have limited options in avoiding of the increases in price. Whereas on the route level increase in price between the two endpoints will increase the sensitivity of the passengers and will divert them on other routes, or will force them to search for possible substitutes of transportation if the geolocation is favorable and the sub-mode transport infrastructure allows for such flexibility (IATA 2008, InterVISTAS 2007).

The inclusion of frequency in the model by the author will result if the less negative value of the elasticity in the study compared to those that decide to omit it from the model.

The base price elasticity of -1,08 obtained from the leisure segment model suggests that the demand is elastic for all studied continents except European. With the help of the continent-specific adjustor elasticity of demand for the latter continent is -0,54, reflecting that the demand is inelastic compared to the North-America continent, Australia/NZ and other continents.

Analyzing the two estimated models both proved that the year of data variable positively affects elasticities, indicating that consumers have become less price sensitive over the year. This was also discovered by Brons et al. (2002).

Studies that used either time-series or cross-sectional data are expected to find less negative estimates, which contradicts the observations of Oum, Waters, and Yong (1990). The authors stated that papers that used cross-sectional analysis showed a tendency to report more negative elasticities compared to the estimates obtained from the time-series data sets.

It is unclear why some studies do not report standard errors since this information is essential to determine the validity of the results. There is no specific theory mentioning why authors avoid to report it or at least provide the information so the reader can calculate it themselves. Nonetheless, both our models imply that the ones who report standard error values on average report more negative price elasticities than the ones who do not. One can assume that in order to publish the result, some authors may avoid reporting the standard error so the reader is not aware of the variation the estimate might inhabit. On the other hand, this might just be a coincidence since 1/3 of the studies that did not report standard errors, also did report standard errors for other estimates in the same study like Brown and Watkins (1968), Dargay and Hanly (2001), InterVISTAS (2007), Saad et.al (1983) and more. However, these are just assumptions and cannot be backed up with any theory.

In addition, we run another regression for the aggregated model where only significant estimates were included to see if there might be any significant change in the intercept and variables. The output showed that all variables reported the same signs, and the majority of them were still significant. The ones who no longer were significant in the model were Long-run, Time-series, and Cross-sectional variables. This indicates that insignificant estimates mostly originated from the cross-sectional or time-series data sets, meaning these variables might be biased in the model. Panel data, however, became significant, indicating that a larger number of significant estimates originated from panel data. The adjusted R2 also increased, partially suggesting that by the inclusion of insignificant elasticities into our sample, the explanatory power of the model becomes reduced, which can explain the low adjusted R2 in our models.

2.6 Limitations and Suggestions for further research

In our thesis, the data set consists of all found elasticities even if they were significant or not in the initial studies. Meaning that all of them have the same weight even though some estimates are not significantly different from zero at a 5% level. It might have impacted on the results, meaning that studies with the low quality of the estimates will have the same impact as the studies with the significant ones. Instead of only using an OLS estimation method, one could, in addition to OLS, use a weighted least squares (WLS) method where weights are given based on the precision of the estimate to control for non-independency in meta-analysis, which has also been recommended by Nelson et al. (2008). Estimates with higher precision will be given a higher weight since these are more representative of the underlying price elasticity population. It might produce different results compared to an OLS estimation since weights are assigned to the studies that represent the population better.

Due to the small sample size and several variables not exceeding ten observations, we were not able to produce a business travellers' model. It would be interesting to see how a business model would look like, and what predictors are essential and how it differs from the aggregated and leisure model if there is any difference.

In our thesis, it was not possible to track down "file drawer" more studies due to time constraints. However, it would be an idea to see if there are any changes in the result if "file drawer" studies are included. However, a considerable amount of time must be used on tracking down and contacting authors that possess these studies. Another option could be to find an adequate method to estimate potential existing literature that is not available to the public. Then two different models could be estimated where one had aggregated every study with both significant and insignificant results, while the other model had only published studies and significant variables and then explore the difference between them. However, to do the first option of contacting authors, one would need considerably more time than six months.

2.7 Conclusion

Investigating the price sensitivity of air passenger transport demand is often seen as an essential part of economic policy. By examining different markets such as fare class, geographical location and market distance, one can determine how price should be adjusted to attract more consumers. There is much disparity in the estimate for price elasticity of air transport across studies. We seek to examine this disparity with the help of a cross-sectional study where meta-analysis techniques are applied. In total, 443 price elasticities of demand for air passenger travel were collected and analyzed.

The empirical results show that there is a base price elasticity that can be estimated.

The estimated base price elasticity of the aggregated model is -0,789, and the base price elasticity of the leisure model is -1,081. The magnitude of the elasticities will vary depending on the methodology used and estimation choices. The most critical determinants were fare class, geographical location, time horizon, year of the data, and different estimation methods. The publication funnel plot shows that there is a publication bias present, and the authors preferer to report negative estimates compared to positive ones. It is also discovered that the estimates that are more negative then the value –0,8 and a positive estimates over 0,05 report lower precision, meaning that policy-makers should be careful when using macro estimates for basis when deciding on future changes in prices.

For further research, it is recommended to apply a WLS method in addition to OLS, since the former enables to assign weights to different studies based on the precision and number of the estimates in the study to control for non-independency in meta-analysis. This thesis did not differentiate between significant and insignificant price elasticity to increase sample size and avoid publication selection bias. A business model was not constructed due to the small sample size, and too few observations per variable. For further research, a disaggregated business model could be built with a larger sample size to investigate essential predictors for the business traveler segment.

For further research, one could spend more time tracking down “file drawer” studies to see if this changes the representation of the expected price elasticity population.

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4.0 APPENDICES

4.1 Apendix A – Included studies

	Autor/Year	Publisher	Geographical scope	Study's mean elasticity	Range	Number of obs. per study	Year of the data set
1	Abate (2016)	Transportation Research Part A: Policy and Practice	Africa	-0,7190	[-0,719]	1	2000-2005
2	Abrahams (1983)	Transportation Research Part A: General	US	-0,6786	[-1,81; -0,08]	7	1973-1977
3	Agarwal and Talley (1985)	International Journal of Transport	US	-0,8030	[-0,8425; -0,7635]	2	1981
4	Baikgaki and Daw (2013)	Mediterranean Journal of Social Sciences	Republic of South Africa	-0,8073	[-0,863; -0,7517]	2	1971-2012

5	Battersby and Oczkowski (2001)	International Journal of Transport Economics	Australia	-0,6200	[-1,68; -0,04]	12	1992-1998
6	Bhadra (2003)	Journal of Air Transportation	US	-1,0278	[-1,816; -0,5576]	11	1999-2000
7	Bhadra (2010)	Journal of the Transportation Research Forum	US	-1,0444	[-1,3015; -0,7596]	3	1999-2000
8	Bhadra (2012)	Journal of the Transportation Research Forum	US	-0,4552	[-0,4552]	1	1990-2010
9	Bhadra and Wells (2005)	Public Works Management and Policy	US	-1,1325	[-1,1325]	1	2000
10	Blunk, Clark, and McGibany (2006)	Applied Economics	US	-0,1922	[-0,1922]	1	1989-2002
11	Boonekamp, Zuidberg, and Burghouwt (2018)	Transportation Research Part A: Policy and Practice	Europe	-0,3826	[-0,6255; -0,1778]	4	2010
12	BOTCE (1995)	Department of Transport, Australian Government	Australia	-0,6277	[-1,86; 0,14]	39	1986-1993
13	BOTE (1986)	Department of Transport, Australian Government	Australia	-0,9496	[-3,54; -0,26]	24	1977-1984
14	Britto, Dresner, and Voltes (2012)	Transportation Research Part E: Logistics and Transportation Review	US	-1,3400	[-1,36; -1,33]	3	2003-2006
15	Brown and Watkins (1968)	Highway Research Record	US	-1,4001	[-2,805; 0,466]	16	1946-1966
16	Castelli, Ukovich, and Pesenti (2003)	Air Transport Research Society World Conference	Europe	-0,8567	[-1,624; 0,884]	10	1999-2002
17	Chi, Koo, and Lim (2010)	Journal of the Transportation Research Forum	US	-2,1397	[-3,303; -1,221]	6	2000, 2005
18	Cigliano (1980)	Business Economics	North Atlantic	-1,3042	[-2,181; -0,447]	6	1965-1978
19	Clewlow, Sussman, and	Transport Policy	Europe	-1,3816	[-3,412; -0,019]	14	1990-2010

	Balakrishnan (2014)						
20	Collins, Hensher, and Li (2010) WIT	Transactions on State of the Art in Science and Engineering	Australia	-1,1878	[-1,1878]	1	2007
21	Dargay and Hanly (2001)	9th World Conference on Transport Research	UK	-0,2875	[-0,58; -0,13]	8	1989-1998
22	De Vany and Garges (1972)	Journal of Transportation Research	US	-1,1000	[-1,10]	1	1980
23	Demirsoy (2012)	Master Thesis / Erasmus University Rotterdam, Erasmus School of Economics	Turkey	-0,0680	[-0,15; -0,0227]	3	1980-2010
24	Dray et al. (2010)	Transportation Research Record: Journal of the Transportation Research Board	Europe	-1,1967	[-1,27; -1,08]	3	2005
25	Dresner, Lin, and Windle (1996)	Journal of Transport Economics and Policy	US	-0,5050	[-0,534; -0,476]	2	1991-1994
26	Ejem et al. (2017b)	International Journal of Business, Management and Allied Sciences	Nigeria	-0,3796	[-0,649; -0,212]	5	2003
27	Ejem et al. (2017a)	International Journal of Research in Management, Science and Technology	Nigeria	-0,9093	[-2,9320; -0,062]	4	2003
28	Falk and Hagsten (2019)	International Journal of Tourism Research	Europe	-0,0708	[-0,109; -0,033]	5	2008-2016
29	Fridström and Thune-Larsen (1989)	Transportation Research Part B: Methodological	Norway	-0,8854	[-1,656; 0,219]	9	1972-1983
30	Fu and Kim (2016)	Journal of Air Transport Management	US	-0,5200	[-0,52]	1	2005-2013
31	Fu, Dresner, and Oum (2011)	Transportation Research Part E: Logistics and Transportation Review	US	-1,1511	[-1,1511]	1	1990-2004
32	Gately (1988)	The Energy Journal	US	-0,1217	[-0,23; -0,03]	6	1965-1986
33	Geslin (2006)	Master Thesis / Massachusetts Institute of Technology	US	-0,5716	[-0,5716]	1	2000-2004

34	Ghobrial (1992)	Journal of Advanced Transportation	US	-1,4460	[-2,587; -0,128]	3	1976-1984
35	Ghoshal (1981)	Transportation Journal	US	-1,6700	[-1,67]	1	1978
36	Gosling and Ballard (2019)	Transportation Research Record	US	-0,9387	[-1,185; -0,0782]	3	1990-2010
37	Granados, Gupta, and Kauffman (2012)	Information Systems Research	US	-0,5850	[-1,03; -0,14]	2	2003-2004
38	Granados et al. (2012)	Decision Support Systems	US	-0,5659	[-0,74; -0,26]	22	2009, 2010
39	Gundelfinger Casar and Coto-Millán (2017)	Revista de Evaluación de Programas y Políticas Públicas	Spain	-0,6000	[-0,60]	1	2011-2015
40	Hakim and Merkert (2017)	Transport Policy	Asia (8 countries)	-0,1130	[-0,113]	1	1973-2015
41	InterVISTAS (2007)	Working Paper Prepared for IATA	US, World regions, UK	-0,9721	[-2,90; -0,10]	19	1994-2007
42	Ippolito (1981)	Journal of Transport Economics and Policy	US	-0,5250	[-0,525]	1	1976
43	Jorge-Calderón (1997)	Journal of Air Transport Management	Europe	-0,6383	[-0,9606; -0,0234]	5	1989
44	Kendall and Jordan (1989)	Transportation Journal	North Atlantic	-0,1397	[-0,209; -0,064]	3	1973-1985
45	Kopsch (2012)	Journal of Air Transport Management	Sweden	-0,8775	[-1,20; -0,5817]	9	1980-2007
46	Maillebiau and Hansen (1993)	Working Paper of University of California	North Atlantic	-0,8813	[-0,915; -0,861]	3	1969-1989
47	Marín (1995)	The Journal of Industrial Economics	Europe	-1,7100	[-1,71]	1	1982, 1989
48	Molloy et al. (2012)	Transportation Research Record	Europe	-0,5273	[-0,674; -0,286]	7	1980-2008
49	Mueller (2015)	Master Thesis, Molde University College	Norway	-0,2169	[-0,8653; 0,8968]	21	1981-2014
50	Mutti and Murai (1977)	Journal of Transport Economics and Policy	North Atlantic	-0,5731	[-1,43; -0,07]	13	1964-1974

51	Nero (1995)	PhD Thesis, European University Institute, Italy	Europe	0,3305	[-0,1119; 0,7729]	2	1993
52	Njoya, Christidis, and Nikitas (2018)	Journal of Transport Geography	Africa	-0,5560	[-0,556]	1	2002-2016
53	Oum, Gillen, and Noble (1986)	Logistics and Transportation Review	US	-1,1523	[-1,1523]	1	1978
54	Rolim, Bettini, and Oliveira (2016)	Journal of Air Transport Management	Brazil	-1,2455	[-2,1086; -0,0122]	16	2003-2013
55	Saad et al. (1983)	Working Paper of Bureau of Transport Economics, Australian Government	Australia	-1,3517	[-3,155; -0,139]	34	1970-1981
56	Schipper, Rietveld, and Nijkamp (2002)	Journal of Transport Economics and Policy	Europe	-1,3000	[-1,33; -1,27]	2	1988-1992
57	Smith and Toms (1978)	Working Paper of Bureau of Transport Economics, Australian Government	Australia	-1,2267	[-1,94; -0,58]	12	1964-1977
58	Sofany (2016)	Master Thesis, Addis Ababa University	Africa	-0,1713	[-0,3015; -0,041]	2	2000-2014
59	Squalli (2014) The	Quarterly Review of Economics and Finance	Dubai (UAE)	-0,7675	[-0,83; -0,70]	4	2007
60	Srinidhi (2010)	South Asian Journal of Management	India	-0,3181	[-0,567; -0,132]	15	2005-2006
61	Straszheim (1978)	Journal of Transport Economics and Policy	North Atlantic	-1,4278	[-2,735; -0,649]	8	1948-1973
62	Talley and Schwarz-Miller (1988)	International Journal of Transport Economics	US	-1,3890	[-1,389]	1	1983
63	Thompson (1974)	Journal of Transport Economics and Policy	UK	-0,7529	[-1,59; 0,25]	7	1960-1969
64	Valdes (2015)	Journal of Air Transport Management	32 countries	0,1051	[0,0983; 0,112]	2	2002-2008
65	Wadud (2014)	Transportation Research Part A: Policy and Practice	US	-0,0965	[-0,10; -0,093]	2	1978-2013
66	Wadud (2015)	Energy	US	-0,2220	[-0,222]	1	1979-2012

67	Wang, Zhang, and Zhang (2018)	Transport Policy	China, India	-1,8975	[-2,60; -1,15]	4	2012-2015
68	Wei and Hansen (2006)	Transportation Research Part A: Policy and Practice	US	-0,8990	[-0,899]	1	2000
	Total			**-0,847**	**[-3,540; 0,8968]**	**443**	**1946-2016**

4.2 Appendix B – List of variables and their description

Variable	Total number of obs.	Description
	Dependent variable data and data on the standard error	
Price Elasticity μ= -0,847; x̃= -0,688 σ= 0,735	*443*	Total number of estimates collected from the studies
Standard error μ= 0,288 x̃= 0,185 σ= 0,364	*352*	Total number of the standard errors collected from the studies

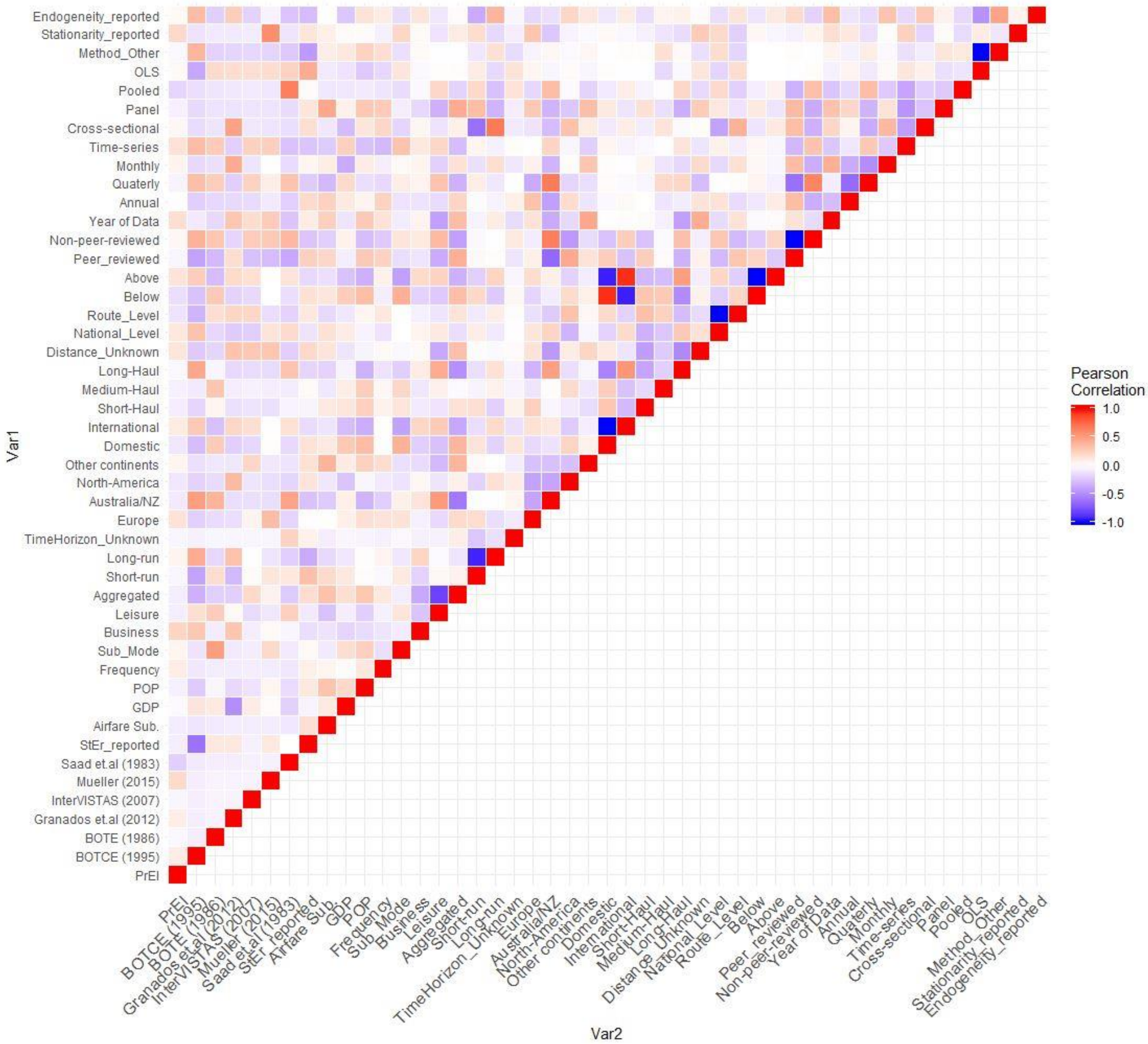
	Independent variables	
StEr_reported	*352*	= 1 if standard error was reported/calculated; = 0 otherwise
Fare	*393*	= 1 if airfare considered in the model; = 0 otherwise
Airfare Sub.	*50*	= 1 if aviation fuel considered as substitute for airfares in the model; = 0 otherwise
INC	*236*	= 1 if income considered in the model; = 0 otherwise
POP	*145*	= 1 if nation population considered in the model; = 0 otherwise
GDP	*137*	= 1 if national GDP, GNP considered in the model; = 0 otherwise
Frequency	*45*	= 1 if frequency considered in the model; = 0 otherwise
Sub_Mode	*57*	= 1 if substitute mode was considered in the model; = 0 otherwise
	Fare class	
Business	*45*	= 1 if elasticity corresponds to business class passengers; = 0 otherwise
Leisure	*154*	= 1 if elasticity corresponds to leisure (economy/discounted) class passengers; = 0 otherwise
Aggregated	*244*	= 1 if elasticity corresponds to total number of business and leisure passengers traveled; = 0 otherwise
	Time-horizon	
Short-run	*278*	= 1 if elasticity pertains to short-run; = 0 otherwise

Long-run	*150*	= 1 if elasticity pertains to long-run; = 0 otherwise
TimeHorizon_Unknown	*15*	= 1 if time-horizon was not specified in the study; = 0 otherwise
	Region/Location	
North-America	*125*	= 1 if study corresponds to North American countries; = 0 otherwise
Europe	*126*	= 1 if study corresponds to European countries; = 0 otherwise
Australia/NZ	*122*	= 1 if study corresponds to Australia and New Zealand; = 0 otherwise
Other continents	*70*	= 1 if study corresponds to other locations; = 0 otherwise
	Route	
International	*245*	= 1 if study corresponds to international flights; = 0 otherwise
Domestic	*198*	= 1 if study corresponds to domestic flights; = 0 otherwise
	Distance, km	
Short-Haul	*108*	= 1 if elasticity corresponds to short-haul market, = 0 otherwise
Medium-Haul	*35*	= 1 if elasticity corresponds to medium-haul market, = 0 otherwise
Long-Haul	*144*	= 1 if elasticity corresponds to long-haul market, = 0 otherwise
Distance_Unknown	*156*	= 1 if distance was not specified in the study, = 0 otherwise

	Data level aggregation	
National_Level	*217*	= 1 if data is aggregated at the national level, = 0 otherwise
Route_Level	*226*	= 1 if data corresponds to route specific level, = 0 otherwise
Below	*185*	= 1 if data excludes international flights, = 0 otherwise
Above	*258*	= 1 if data includes international flights, = 0 otherwise
	Publication type/Quality	
Peer_reviewed	*274*	= 1 if the study is a published journal article, = 0 otherwise
Non-peer-reviewed	*169*	= 1 if the study is a master thesis, working or conference paper, = 0 otherwise
	Data set	
Pub_Year	*2001*	Average year of all collected studies
Data_Set	*1994*	Average year across all observations
Annual	*143*	= 1 if annual data used to estimate demand; = 0 otherwise
Quarterly	*198*	= 1 if quarterly data used to estimate demand; = 0 otherwise
Monthly	*96*	= 1 if monthly data used to estimate demand; = 0 otherwise
	Data type	
Time-series	*195*	= 1 if time-series data used to estimate demand; = 0 otherwise
Cross-sectional	*82*	= 1 if cross-sectional data used to estimate demand; = 0 otherwise

Pooled	*73*	= 1 if pooled data used to estimate demand; = 0 otherwise
Panel	*93*	= 1 if panel data used to estimate demand; = 0 otherwise
	Functional form	
Log	*433*	= 1 if double-log model used to estimate demand; = 0 otherwise
Other_functional	*10*	= 1 if other functional form model used to estimate demand; = 0 otherwise
	Methodological variables	
OLS	*268*	= 1 if OLS regression method was used to estimate demand; = 0 otherwise
Method_Other	*175*	= 1 if other regression method was used to estimate demand; = 0 otherwise
	Treatments	
Stationarity_reported	*57*	= 1 if data stationarity was addressed by the authors; = 0 otherwise
Stationarity_untreated	*386*	= 1 if data was not transformed into stationary; = 0 otherwise
Endogeneity-reported	*193*	= 1 if endogeneity was addressed by the authors; = 0 otherwise
Endogeneity_untreated	*250*	= 1 if endogeneity was not considered by the authors; = 0 otherwise

Appendix1



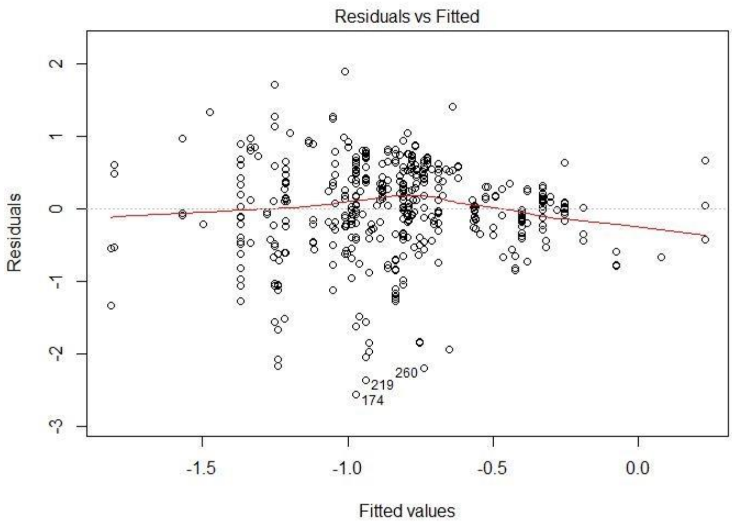
Correlation matrix for aggregated model

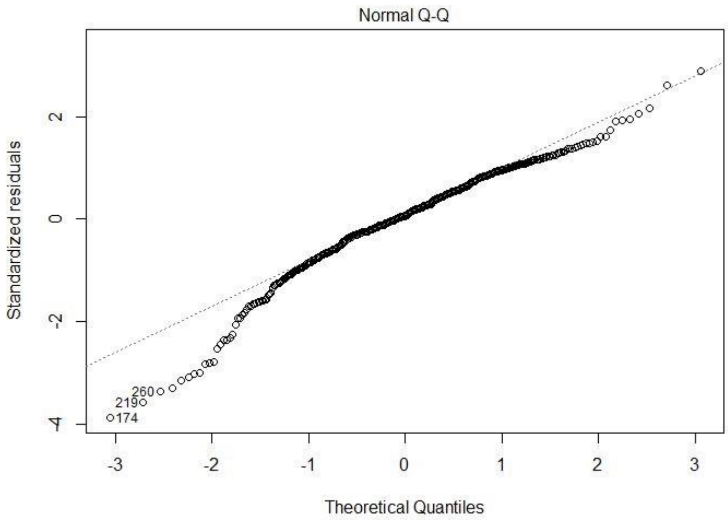
Appendix 2 large model

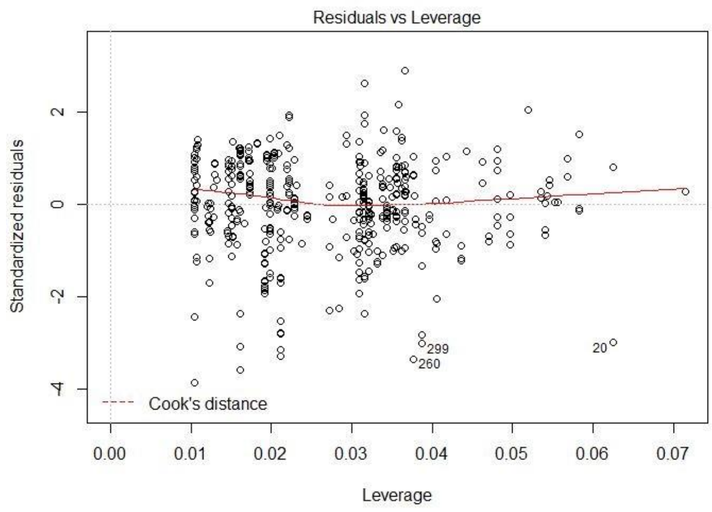
```
Residuals:
     Min       1Q   Median       3Q      Max 
-2.59562 -0.29103  0.05852  0.38076  2.06413 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             -0.690216   0.291177  -2.370 0.018230
`BOTCE (1995)`           0.295324   0.315222   0.937 0.349374
`BOTE (1986)`           -0.492117   0.287094  -1.714 0.087263
`Granados et.al (2012)` -0.087724   0.281182  -0.312 0.755213
`InterVISTAS (2007)`    -1.378688   0.376805  -3.659 0.000286
`Mueller (2015)`        -0.892481   0.338900  -2.633 0.008772
`Saad et.al (1983)`     -0.645770   0.223218  -2.893 0.004020
`Airfare Sub.`          -0.244926   0.138365  -1.770 0.077447
GDP                     -0.056925   0.113771  -0.500 0.617101
POP                     -0.071247   0.106301  -0.670 0.503087
Frequency                0.254404   0.131255   1.938 0.053281
Sub_Mode                 0.235712   0.144825   1.628 0.104387
Business                 0.287998   0.153410   1.877 0.061186
Leisure                 -0.104013   0.124357  -0.836 0.403413
`Short-run`              0.161428   0.221457   0.729 0.466457
`Long-run`              -0.359669   0.245647  -1.464 0.143917
Europe                   0.232577   0.155526   1.495 0.135575
`Australia/NZ`          -0.254007   0.196234  -1.294 0.196255
`Other continents`       0.452100   0.169866   2.662 0.008085
`Short-Haul`            -0.056835   0.139499  -0.407 0.683911
`Medium-Haul`           -0.074135   0.187633  -0.395 0.692969
`Long-Haul`             -0.417270   0.165791  -2.517 0.012223
Route_Level             -0.273527   0.114005  -2.399 0.016875
Above                    0.328593   0.123967   2.651 0.008346
Peer_reviewed           -0.418244   0.196146  -2.132 0.033576
`Year of Data`           0.005795   0.005712   1.014 0.310973
Monthly                 -0.325477   0.171507  -1.898 0.058433
Annual                  -0.312503   0.171685  -1.820 0.069458
`Time-series`            0.343754   0.186833   1.840 0.066507
`Cross-sectional`        0.661174   0.248305   2.663 0.008056
Panel                   -0.248863   0.180473  -1.379 0.168664
OLS                      0.257461   0.113318   2.272 0.023603
Stationarity_reported    0.125375   0.139100   0.901 0.367945
Endogeneity_reported     0.025861   0.124387   0.208 0.835403
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6563 on 409 degrees of freedom
Multiple R-squared:  0.2627,	Adjusted R-squared:  0.2033 
F-statistic: 4.417 on 33 and 409 DF,  p-value: 2.496e-13
```

Appendix 3 test diagonostic for aggregated model

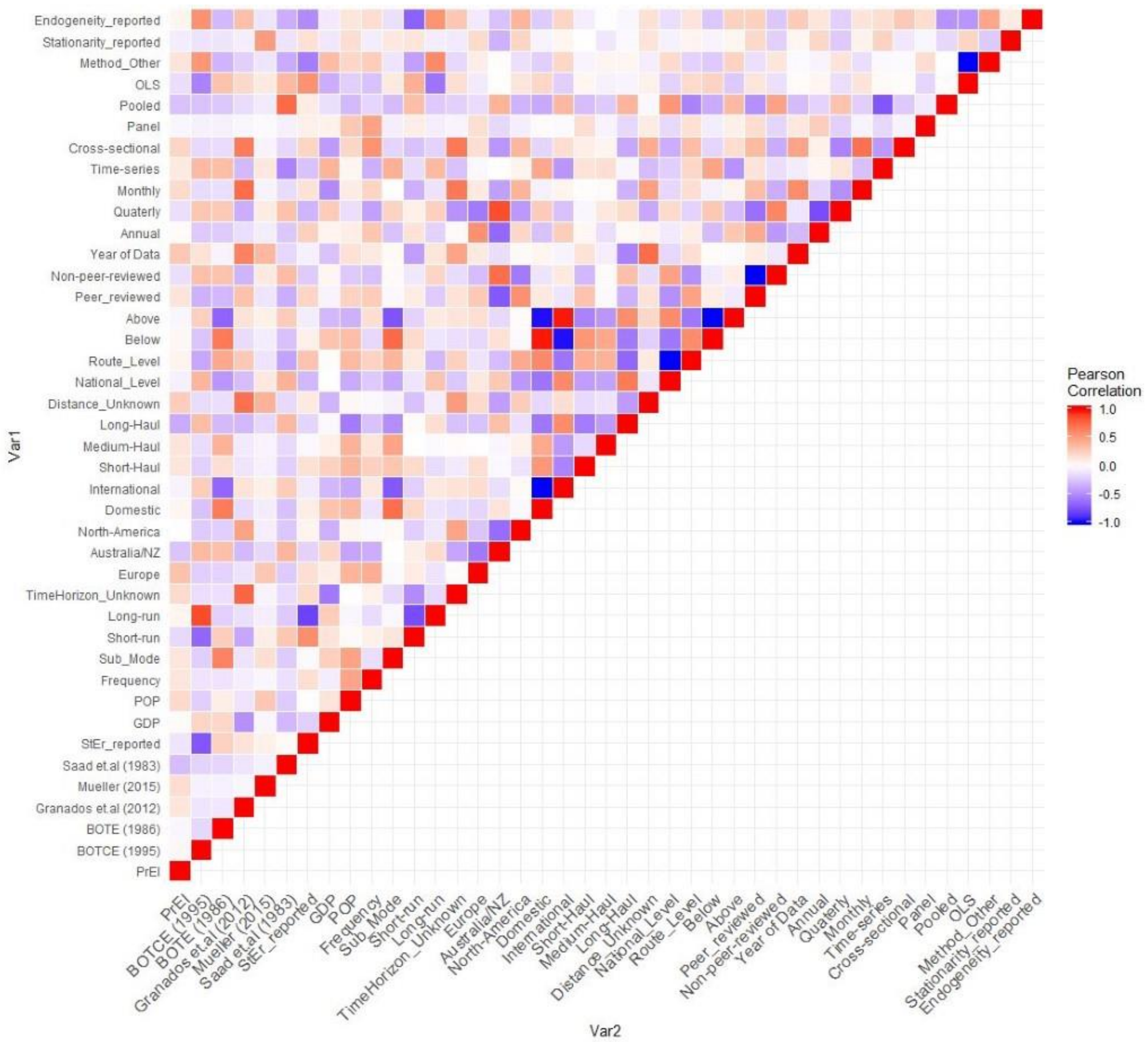
```
        studentized Breusch-Pagan test

data:  reg_exSt
BP = 41.406, df = 11, p-value = 2.052e-05
```







Appendix 4 correlation matrix for leisure data



Appendix 5/ page 1 leisure large model

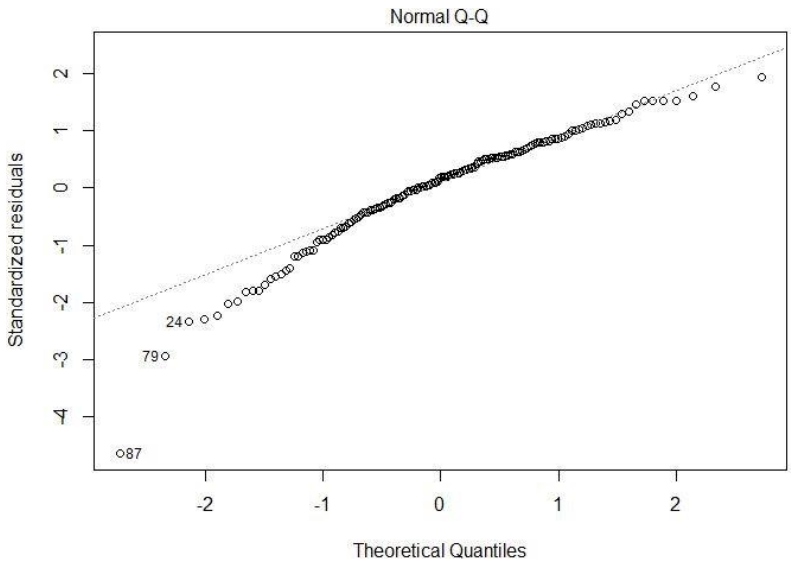
```
Residuals:
     Min       1Q   Median       3Q      Max 
-1.70171 -0.27950  0.04251  0.29487  1.00000 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)               2.97693    8.26023   0.360  0.71916
`BOTCE (1995)`            0.37224    3.39322   0.110  0.91282
`BOTE (1986)`            -1.12668    0.78511  -1.435  0.15377
`Granados et.al (2012)`   4.01587    5.77161   0.696  0.48785
`Mueller (2015)`         -4.17497    3.18019  -1.313  0.19165
`Saad et.al (1983)`      -0.01559    2.67340  -0.006  0.99536
StEr_reported            -0.64959    0.22383  -2.902  0.00438
GDP                      -0.02838    0.17787  -0.160  0.87348
POP                       0.12748    0.24782   0.514  0.60788
Frequency                 2.73330    2.99107   0.914  0.36257
`Short-run`              -0.71248    4.59682  -0.155  0.87708
`Long-run`               -1.46919    4.56808  -0.322  0.74828
Europe                    0.32306    0.41244   0.783  0.43494
`Australia/NZ`           -0.75010    1.50732  -0.498  0.61961
`Other continents`        0.48101    1.15658   0.416  0.67821
`Short-Haul`             -1.04546    2.44917  -0.427  0.67021
`Medium-Haul`            -1.27122    2.44380  -0.520  0.60386
`Long-Haul`              -2.24428    2.44127  -0.919  0.35971
Route_Level              -0.75573    0.58757  -1.286  0.20075
Above                     0.52096    1.84591   0.282  0.77824
Peer_reviewed            -0.80987    1.52589  -0.531  0.59653
`Year of Data`           -0.04720    0.13895  -0.340  0.73467
Monthly                  -2.72026    1.15534  -2.355  0.02011
Annual                   -1.67107    1.27500  -1.311  0.19238
`Time-series`             2.12699    1.22198   1.741  0.08421
`Cross-sectional`         1.50595    0.53828   2.798  0.00596
OLS                       0.03301    1.87932   0.018  0.98601
Stationarity_reported     1.14948    1.76675   0.651  0.51649
Endogeneity_reported     -1.46840    2.33285  -0.629  0.53021
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Residual standard error: 0.5163 on 125 degrees of freedom
Multiple R-squared:  0.4887,	Adjusted R-squared:  0.3742 
F-statistic: 4.268 on 28 and 125 DF,  p-value: 9.849e-09
```

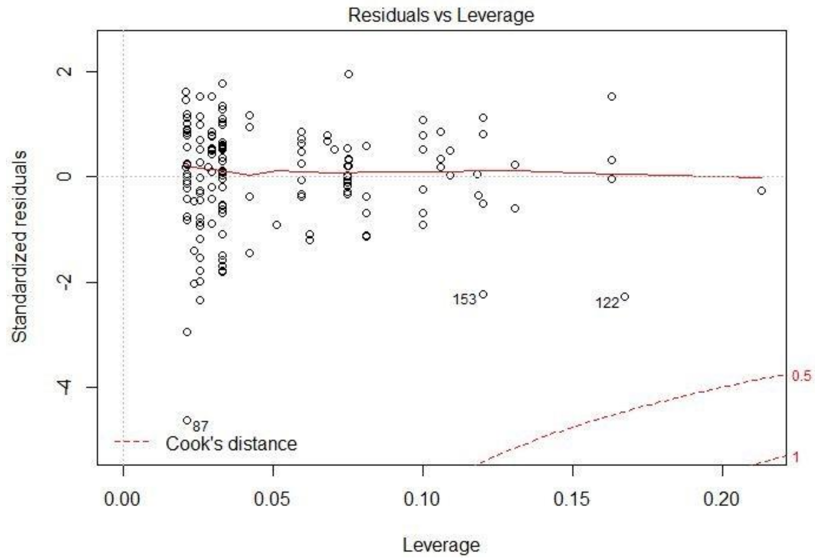
Appendix 6 optimal leisure model

```
Residuals:
     Min       1Q   Median       3Q      Max 
-2.64336 -0.28812  0.04063  0.39812  1.04933 

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          -0.546637   0.254848  -2.145  0.03365 *  
`Saad et.al (1983)`  -0.511937   0.191593  -2.672  0.00842 ** 
StEr_reported        -0.689034   0.197113  -3.496  0.00063 ***
Frequency             0.321126   0.306029   1.049  0.29580    
`Long-run`           -0.612177   0.242302  -2.527  0.01261 *  
Route_Level          -0.255231   0.136798  -1.866  0.06413 .  
`Year of Data`        0.020738   0.007712   2.689  0.00802 ** 
`Time-series`         0.283183   0.191241   1.481  0.14087    
Panel                -0.093620   0.598574  -0.156  0.87593    
`Cross-sectional`     1.070048   0.420612   2.544  0.01202 *  
Endogeneity_reported -0.319923   0.161795  -1.977  0.04993 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.581 on 143 degrees of freedom
Multiple R-squared:  0.2594,	Adjusted R-squared:  0.2076 
F-statistic: 5.009 on 10 and 143 DF,  p-value: 3.149e-06
```

Appendix 7 test diagonostic for optimal leisure model

```
	studentized Breusch-Pagan test

data:  reg_exLeis2
BP = 4.187, df = 7, p-value = 0.758
```


Normal Q-Q
Standardized residuals
Theoretical Quantiles
24
79
87
-2
-1
0
1
2
-4
-3


Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
153
122
87
0.5
1
0.00
0.05
0.10
0.15
0.20

Appendix 8 publication bias plot