CHARLES UNIVERSITY

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The Key Determinants of Plane Ticket Price Dispersion

Bachelor thesis

Prague 2017

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Academic Year: 2016/2017

Declaration of Authorship

1. The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

2. The author hereby declares that all the sources and literature used have been properly cited.

3. The author hereby declares that the thesis has not been used to obtain a different or the same degree.

Prague 31. 7. 2017 Radka Vlčková

Acknowledgments

I would like to express my gratitude to my friends and family who have been supporting me every day for whole 4 years. Moreover, I am grateful to my supervisor, Mgr. Ing. Adam Kučera, for his patience and for his dedicated precious time.

Bibliographic note

VLČKOVÁ, Radka. (2017). *The Key Determinants of Plane Tickets Price Dispersion*. 55 p. Bachelor thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies. Supervisor Mgr. Ing. Adam Kučera

Range of thesis: 61 496 characters (with spaces)

Abstract

This thesis examines the plane tickets price development using both descriptive evidence and econometric analysis. The observed phenomenon of rising and falling fares in period close to departure is described and compared with the extensively developed theories, such as demand utilization and stochastic peak load pricing. Studying the fares observed on European routes using descriptive evidence revealed that the airlines accommodate fast to the uncertain demand. In the econometric part, the key factors influencing the price dispersion are determined. The contribution of this thesis is mainly in the econometric approach, as the price fluctuations are measured weekly using the coefficient of variation. This made it possible to compare how the different flight or market characteristics affect price dispersion in different week to departure. It was shown that number of sold seats, the load factor, is the crucial factor.

Keywords

Price dispersion, airline market, key determinants, European aviation

Abstrakt

Tato práce se zabývá vývojem cen letenek s využitím deskriptivních a ekonometrických analýz. Pozorovaný fenomén stoupajících a klesajících cen v období blížícím se odletu je popsán a porovnán s rozsáhle rozvinutými teoriemi, jako je využití poptávky a stochastické stanovování cen na základě vysoké poptávky. Studium cen letenek na evropských trasách s použitím popisných technik ukázalo, že letecké společnosti se dynamicky adaptují na nejistou poptávku. V ekonometrické části jsou určeny klíčové faktory ovlivňující rozptyl cen. Tato práce přispívá k dosavadnímu výzkumu hlavně ekonometrickým přístupem; kolísání cen je měřeno týdenně s použitím variačního koeficientu. To umožnilo porovnat, jak různé letové nebo tržní vlastnosti ovlivňují rozptyl cen v různých týdnech před odletem. Bylo ukázáno, že rozhodujícím faktorem je počet prodaných míst, tj. míra obsazenosti.

Klíčová slova

Cenový rozptyl, letecký trh, klíčové determinanty, evropské letectví

Bachelor thesis proposal

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Proposed Topic:

The key determinants of plane ticket price dispersion

Preliminary scope of work:

Research question and motivation

The thesis is concerned with the key determinants of plane tickets price development. I want to investigate the variation of ticket prices in the period from the moment they are released by an airline company to the last moment they are available for purchase online. My goal is to compare ticket prices of main European flight routes and as many European airlines as possible, identify the main factors determining variation in plane ticket prices, and understand how much and why they impact the prices.

Multiple academic papers investigate dispersion of prices of plane tickets, but the authors often restrict their analyses only to a limited set of determinants. Articles usually focus on the non-EU airline market or just on a few countries. Articles concerned with airline industry price-setting cover the time period of price changes typically containing many years. I want to focus on price changes within one year, possibly the latest years as the airline industry is developing rapidly. We can expect the industry to grow in the future, which is another reason to focus my thesis such way.

Contribution

Main contribution is overall investigation of European airline industry via differences in its price-setting policies. The thesis will cover complexity of the price determination process and possible factors influencing the price variance. Among the practical importance, this will contribute to understanding the microeconomic forces leading to effective markets.

Methodology

Firstly, I am going to set a theoretical background of plane ticket price development, outline reasons for the particular dynamics and the motivation of airlines. Then I want to compare the theory based on academic literature with outputs of econometric models. I will use the data collected and kindly provided for my research by kiwi.com.

Outline

Abstract

Introduction – background, brief description of known theory, what is the gap I am going to fill

Literature review – main relevant literature I am going to build on during the thesis

Theoretical part – defining the relevant theory, models, and key concepts, describing the relationships I would like to examine in the next part

Empirical part – analysis of the data provided by econometric models

Results – interpretation of results obtained by models and comparing with theoretical part, commenting on the comparison

Conclusion

Bibliography, appendixes, tables, and graphs at the end

List of academic literature:

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Contents

1. Introduction

Since the full deregulation of European airline market in 1990´s the airline services for public has evolved rapidly mainly due to the entrance of new airlines. These have served as the competitors to the traditional, legacy airlines. Because of this emergence all the market players had to adapt to different market conditions by creating more sophisticated price-setting methods, or in other words yield management. The strategies can be divided into two large groups: some companies lowered the overall costs, from on-board service to maintaining the offices, whereas the other ones developed a complex system how to differentiate its product to increase revenues. These strategies are used by companies which are known as low-cost carriers (LCC) and full-service carriers (FSC), respectively. What is characteristic for civil aviation is that costs can only be variable in the long run, whereas in the short run, most of the costs are fixed. It implies that yield management is restricted to revenue management. Second specification of airline companies is the product; the good is perishable, it expires at a given date, there is only specific amount of time for consumers to buy. Moreover, the firms face heterogenous demand, uncertain aggregate demand, and different price sensitivity of customers. All these specifications suggest that firms may develop dynamic pricing strategies which effectively increase their revenues.

This thesis aims to follow the papers about fluctuations among the daily prices of flight tickets. The published literature has extensively examined the airfare dispersion as well as the various variables affecting it. Flight ticket prices fluctuation can be analysed in terms of cross-sectional properties or from the time to departure point of view. The latter approach is represented by Mantin & Koo (2009). Their study focuses primarily on dominant factors affecting the prices and how the importance of those factors changes prior to departure. The cross-sectional approach represented by Alderighi (2012), Gaggero (2011) and Piga (2006) tries to explain broadly different price dispersion either by LCC and FSC characteristics or by using market characteristics and various indexes that measure market structure.

This thesis builds on the first approach. The purpose of this thesis is to explain the intra-temporal price variations of a particular flight, with emphasis on the revision of the effect of different price-setting of LCC and FSC. In practice, at first the relevant explanatory variables are gathered, both gathered from the literature as well as some newly proposed.

Afterwards, we use least squares methods to explain the price dispersion by variation of the explanatory variables. However, afterwards, we focus on the time aspect. The model is estimated separately for various number of weeks to departure, and the results are compared.

After the first introductory section, the thesis is structured as follows:

The second section provides brief overview of deregulation of the aviation market which is followed by a detailed summary of the findings about price dispersion, the principal factors affecting it and the influence of time. The data, its collection and descriptive evidence of the fares are provided in the third section. In the next section, the model as well as the variables are described. The results are presented in section five and conclusion and further discussion close this thesis.

2. Motivation and literature review

2.1. History of deregulation

Until the late 80´s the airlines in Europe as well as almost all around the world had been state-owned and mostly government-subsidized. Airlines had operated monopolistically in their domestic markets and under regulations internationally (Belobaba, 2009). In 1986 the signature of Single European Act marked the beginning of the liberalization of the airline industry; the European airline market was deregulated and liberalized in 3-stages (European Parliament, 2017). The third stage removed last barriers for commercial market but in the same time some basic rules for establishing and maintaining the airline business were settled (Alderighi, 2012). The market has allowed free entry and exit and freedom in setting of the fares. These conditions led to the emergence of a new type of competition that has been imposed to the traditional airlines by carriers which cut both the costs and the fares. Effects of these steps could be already seen in 1997 when about 12 airlines operated low-cost flights following the example of Southwest Airlines, the pioneers of low-cost aviation still operating in the US market. On the other side, only 3 state-owned airlines were privatized leaving the rest of European carriers on governments subsidies (The Economist, 1997). Since the deregulation, the airlines in Europe have operated under the so-called Chicago Convention, formally Convention on International Civil Aviation.

The national flag-carriers operated in a system known as “hub-and-spoke” which enabled a single airline to serve many airports, to join demand for specific connections into a flight leg with hub as a centre. In other words, instead of scheduling many direct flights connecting different airports, the carrier offered more one-stop flights with a layover in the hub; this costly system can be described as a hub-spoke-hub roundtrip for the plane. This approach was expensive since it required intensive organization of flights in the hub. In the time when IT technology was not much developed the hub-and-spoke system needed a lot of staff. The deregulation brought some benefits for passengers as the flag carriers formed themselves into full-service carriers. For example, it lowered the time the passenger spent in the hubs (Gillen & Morrison, 2003); (Belobaba, 2009).

The relaxed market conditions were used by emerging LCC whose strategy stands on unified product, service, and radically decreased costs of operation, which is their

competitive advantage, too. To be specific, they operate direct flights from and to the secondary airports which provide worse and cheaper service. The fleet is often unified and busier, as more flights a day than the FSC are scheduled. This approach lowers the charges paid to the airports, because the planes stay less time, and the aboard crew is busier (Gillen & Morrison, 2003); (Alderighi, 2012). Pels and Rietveld (2004) state that LCC target the price sensitive part of the demand, so called leisure travellers. But when some time passed by, it was no longer unusual that business passengers, after calculating pros and cons of low-cost flying, started to use LCC. Therefore, traditional airlines, former or still national flag carriers, had to react to pricing strategies of their competitors.

2.2. Factors beyond the price dispersion in airline industry

The existing literature follows few main directions of research identifying the characteristics affecting and causing the price dispersion (PD). According to Borenstein and Rose (1994), whose article has become a basis for many researches after its publication, the variation of price is influenced by market structure, frequency of flights on a route and price-elasticity of consumers. At the end, they suggest the price discrimination and peak-load pricing as a factor influencing magnitude of PD.

Price discrimination

Price discrimination is the business practice of selling the same good at different prices to different consumers when these differences in prices are not justified by cost inequalities (Mankiw, 2011). Price discrimination has been used as an efficient tool for distinguishing the customers and more importantly their willingness to pay. Price discrimination might be the reaction of airlines to fixed capacity of the planes with uncertain aggregate demand, or might emerge as ananswer to the competitive environment (Alderighi, 2010); (Giaume & Guillou, 2004). For instance, the division of planes into classes, member loyalty system, advance-purchase discounts – this is an example of inter-temporal price discrimination - are the most common technics. The LCCs adopt only some of the price discrimination tools since they exclude the division based on quality (Piga & Bachis, 2006). When the market structure is considered then in the monopolistic and duopolistic markets the companies seem to price discriminate very easily (Gaggero & Piga, 2011). However, the findings need additional explanation: the

routes examined in the article are operated mainly by LCC and the authors are only interested in inter-temporal price discrimination which is not based on any restrictions for the passengers. The inter-temporal price discrimination means that airlines use the fact that consumers are willing to pay more for a ticket as the departure nears. So, the consumers are charged different, mostly higher fare according to the number of days prior to departure (Alderighi, et al., 2011) (see section 2.3). Different findings are provided by an article by Giaume & Guillou (2004) who conclude that price discrimination increases with higher competition on the market. The airlines try to attract the consumers with low willingness to pay by offering them sales on restricted amount of flights. Those customers are price sensitive and do not have departure day and time specifications.

Peak-load pricing

Alderighi (2010) provides theoretical explanation of PD under peak-load pricing. Peak-load pricing is "a pricing system in which customers or passengers using a utility or service at a time of peak load are charged more than those using it off-peak" (Oxford dictionaries). This definition suits both "systematic" and "stochastic" peak-load pricing (PLP). As Alderighi explains, the systematic PLP is planned because the peaks are known – Christmas, summer holidays. The difference between PLP and price discrimination is justification by costs. The PLP is based on uncertainty in demand and the cost connected to it. He takes the evidence from authors who did empirical research of CV, using namely the coefficient of variation or Gini index, and tries to find out how much of the variation can be explained by PLP. In his model of PLP he concludes that when uncertainty of demand is high the PD is high as well, but for small uncertainty, the PD persists on the small values.

Yield management

Airlines have developed a pricing policy which involves changing the prices of perishable goods, the seats in scheduled flight, to adapt to an unknown demand. This is referred to as a yield management (YM). The goal is to maximize the sales. As mentioned above, a big part of the cost is fixed in the aviation therefore when management maximizes sales, they maximize the profits. Let's adapt to the airline's point of view. If the goal is to maximize the profits then the load factor (LF), ratio of occupied seats to the number of

all seats in the plane in the time of departure, should reach 100% and all the tickets should be sold at the price equal to reservation price of given customers, in the best scenario. Usually, the seats are grouped into quality segments or into parts with different service provided. Those segmentations help to determine passenger´s reservation price and preferences. Based on this distribution the airlines coordinate the price levels. Bilotkach, et al. (2015) contribute to the literature of YM by studying the effectiveness of YM interventions. Thanks to a very large and rich data set they could find out that high fare decrease, which is a sign of personal intervention of a yield manager, is an indication of bad demand realization in that given flight/route. As a result, decrease of one standard deviation of price leads to 2.7% increase of load factor on average. On leisure-passenger market the price interventions are counterintuitively ineffective, at least with this data set. The provided explanation is that leisure passenger buys the flight ticket in advance and so they are not affected by sales shortly before departure.

Demand uncertainty and capacity utilization

Another market specifications that affect PD examines Bilotkach (2005): the demand uncertainty and capacity constraints. The analysis of data collected on London – NY route in his article shows that high PD appears on the routes aimed at business travellers while rather uniform fares are set for leisure travellers. The routes can be defined as big-city routes and leisure routes. For distinguishing the type of the routes, the difference in January temperatures between origin and destination is used as an example (Gerardi & Shapiro, 2009). He concludes that the short-term capacity seems to positively contribute to PD of last-minute fares which is consistent with yield management theories, however every future researcher should be aware that capacity constraint is not proved to be the source of PD. What they observe for airlines with high market share is lowering of fare shortly before the date of departure which means the airline would rather sell free seats for sure than wait for a consumer who is ready to pay the high price. Further research in this direction, but in US market, is done by Escobari & Lee (2014) who build the theory of demand realizations for limited capacity in a competitive market. They state that the prices are set in advance based on the distribution of demand states. This is connected to the yield management which is discussed in the previous section. In fact, the demand can only be predicted from experience. The paper empirically proves the theory, i.e. the

negative relationship between volatility in the distribution of demand states and the capacity utilization. They explain: as the price grows with high demand realizations, the last people with their reservation price are discouraged by the high fares therefore the volatility of demand contributes to lower average sales. In numbers, rise of 1 standard deviation of unexpected demand for a given flight implies 21% decrease of capacity realizations. It is interesting that 6.7% increase of capacity utilization saves 2.7 billion US dollars for the entire US industry (Dana & Orlov, 2014).

Market structure

Since the deregulation, the market structure has played significant role in research of PD. One of the larger articles on this topic presents Gerardi & Shapiro (2009). The authors have been collecting data for 13 and half years. Based on the data set they can conclude that higher competition is associated with decrease in PD. Further, they sum up the following:

a. On markets with even mix of business and leisure travellers the PD is the most decreased. It is due to the significant reduction of the higher fares and a bit smaller decrease of prices from the bottom of the price variation.
b. The competition affects PD much less on routes occupied mainly by leisure travellers.

Thanks to the data set they found that there is a connection between business cycle and PD via effect of competition. The influence of competition on PD is softened during troughs of business cycle.

For any examination, either theoretical or empirical, there is a need to define different market structures in aviation terms. Alderighi, et al. (2012) introduce the clasification to monopoly, symmetric duopoly, asymmetric duopoly, and asymmetric oligopoly according to the number of FSC and/or LCC in the market.

Monopoly	1 FSC
Symmetric duopoly	2 FSC
Asymmetric duopoly	1 FSC and 1 LCC
Asymmetric oligopoly	2 FSC and 1 LCC

TABLE 1 – Structuring the aviation market according to the number and type of carriers operating on it. Source: (ALDERIGHI, 2012)

However, in empirical examination they use Herfindahl-Hirschman Index (HHI) which is a measure of market concentration. The results of their work are that the PD is reduced in the market with competing FSCs where markets with majority of business travellers are more affected. Moreover, on the asymmetric duopoly market, all the fares get flatter and lower in comparison to monopoly. The biggest decrease of fares is recognized for asymmetric oligopoly, again in respect to monopoly.
The different findings present Giaume & Guillou (2004) who study market concentration in terms of market inequality; they conclude that higher market inequality decreases level of prices. This is characteristic for the European area in 00´s; FSC with big market share faces low prices of entrancing LCC.

2.3. Inter-temporal price dispersion

So far, the factors affecting price dispersion across routes and flights have been discussed. Few authors, however, attempt to discover the properties which have an influence on the dynamic price dispersion. Dynamic price dispersion is defined as the accumulation of fare variations across fare histories (Mantin & Koo, 2009).

Numerous articles about dynamic pricing or dynamic PD exist. Even though most of them are empiric and therefore based on the real data, it is a common issue that data sets are provided sporadically; the data are obtained from companies which store the crucial data for research. Considering this, researchers either collect the data on their own using web spiders[1], or ask for data just few airlines resulting in limited data sets.

Motivation for studying the dynamic evolution of airfares differ across studies. It provides a suggestion about airline pricing techniques from which the customers can benefit or the articles provide insight into uncertain demand and capacity constraints and how the airlines cope with these phenomena. Other articles examine how different types of airline companies react to each other in terms of prices and services and some research is directly focused on the varying business models within competing environment. Following

[1] Web spider is a program accesing various web sites and collecting important data automatically.

chapter summarize the main findings. For clarity, it is distinguished between US and EU market.

Rising prices of an airline ticket day by day are commonly observed worldwide. It is found by Alderighi, et al. (2011) that on London-Amsterdam route the prices of 2 major FSC airlines flights increase about 3% on average with the sharpest increase, circa 80%, during the last days before the day of departure. Similar findings are presented by Malighetti, et al. (2009) as they suggest that price trends seem to resemble a hyperbola as the day of departure nears. Evidence from the US market is basically consistent with the approach of European airlines, even though the US data set shows slightly different marks when the day of departure is close - the prices fall as there is less time to sell last free seats (Escobari, 2012).

Gaggero & Piga (2011) and Malighetti, et al. (2009) study the effect of level of competition on inter-temporal prices. Malighetti uses the number of providers on the same European routes as the measure of competition and the result is that the competition is positively correlated with dynamic pricing. Authors suggest that airlines, rather than lowering prices, adopt advance sales which rises PD. Gaggero and Piga conclude differently. Using HHF index as the measure of market concentration and the Gini coefficient representing price dispersion, the empirical evidence is in favour of monopoly effect. High market power allows to distinguish between the price elastic and the price inelastic passengers.

In Gaggero & Piga (2011) a reader can find nice piece of information about PD when the departures are grouped around international holidays. During these high demand periods, the fares are less dispersed and on average higher with comparison to common days. This is consistent with inter-period price discrimination strategy.

Finally, the article closest to empirical work done in this thesis is written by Mantin & Koo (2009) . Unfortunately, their research includes only US airline data. They conclude as follows:

"The empirical analyses reveal that the price dispersion, and its dynamic change, critically depends on variables that characterize the route, such as population, income, and the business index. In that respect, it surprising to find that competition intensity is

not a significant variable in explaining the price dispersion. Rather, it is the combined market share of LCCs that helps predicting the price dispersion and accounts for traveller's composition." (Mantin & Koo, 2009)

3. Data

3.1. Data collection

The fares are collected manually by the author. The data set consists of daily fares on 4 non-stop routes of both directions, but not for the round-trips: Prague-Venice, Prague-Brussels, Berlin-Madrid, and Berlin-Tenerife. These destinations are chosen carefully to cover the characteristics that will be used in the econometric estimations and to improve the ability to interpret the results. The goal, when selecting the routes, is to avoid any influence that cannot be covered.

In Prague, Venice, or Tenerife there is not based any large airline which would provide connection to non-European countries. In other words, neither Prague, Venice nor Tenerife are important hubs. Even though airlines based in Brussels, Madrid or Berlin provide connections all over the word, it is very unlikely that a traveller would choose more complicated flight connections if there exist more flexible ones. Nevertheless, the absence of favourable hubs ensures that the destination is the final one for the travellers in most cases and so the travellers do not continue to other destinations by plane. Prague-Venice and Berlin-Tenerife represent routes occupied by price-sensitive leisure travellers; on the other hand, Prague-Brussels and Berlin-Madrid are both routes rather for business travellers. On the major business routes, the flights are operated frequently mainly by former flag carriers or by FSC while many airlines operate few flights a week on the leisure routes. This follows the graphical representations in Table 2 and Table 3. It can be seen that the Prague-Venice and Berlin-Tenerife routes are operated by numerous airlines, but the rest of the days in week are not presented, and on Prague-Brussels and Berlin-Madrid routes the frequency is much higher. The prices of the tickets are collected daily over 58 days. That does not include the day of departure (14/6/2017 and 20/6/2017) and 1 day before the departure because a lot of the observed flights sold out all the tickets and therefore no price was shown on the airline's websites. The departure day itself is weekday, not a holiday or weekend which would affected the PD (see section 2.3). The one-day frequency covers dynamic environment of price-setting policies. Also, every

route is represented by both LCC and FSC in varying ratios where LCC is either Ryanair, SmartWings or EasyJet (ICAO, 2017). To keep the data collection clear, only

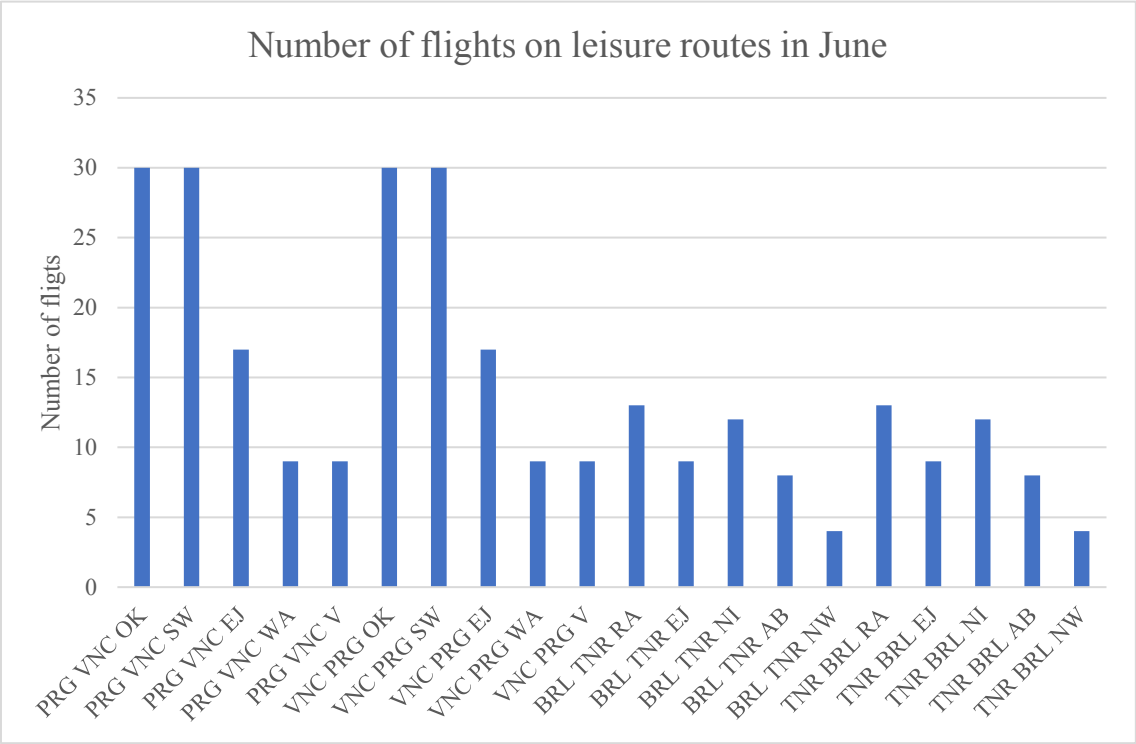

TABLE 2 - Number of scheduled flights in June 2017 – leisure-traveller routes; the abbreviations mark origin, destination, and carrier

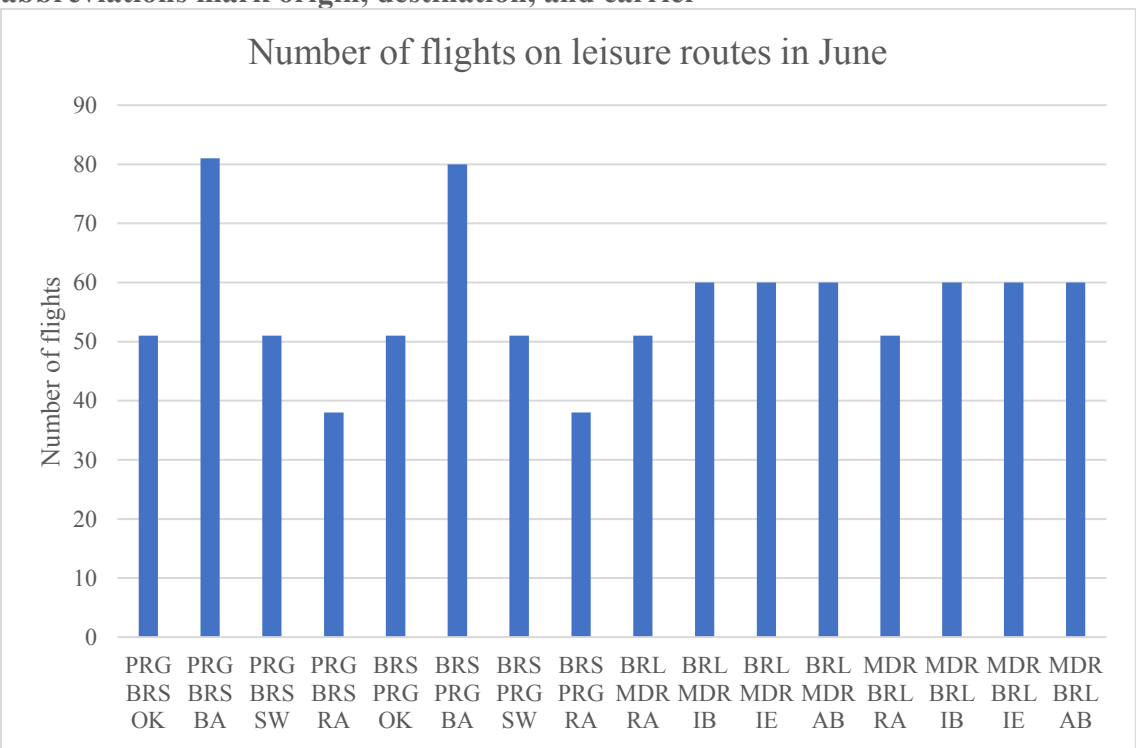

TABLE 3 - Number of scheduled flights in June 2017 – business-traveller routes; the abbreviations mark origin, destination, and carrier

the lowest fares offered are recorded. For example, Ryanair stick to its low-cost strategy and provide simply 1 fare. But the legacy carriers offer usually 3 types of service with different fares in 2 categories: Economy and Business. So, the observations consist of the cheapest fares solely.

3.2. Flights description

In this section, some characteristics of the flights are presented; the variables used in the models will follow this description.

So far, the data is split into groups according to the route and the direction. However, publicly open sources can tell much more than one can read on the airlines website. For example, www.flightradar24.com watches over every civil flight on the planet and provides exhaustive reports about the flights, planes, or airlines. The data about frequency of flights operated by one carrier on monitored routes are obtained from this website. Info, whether the given airlines are FSC or LCC, is collected from an official document issued by International Civil Aviation Organization (ICAO). Several characteristics about the service included within the price of the cheapest plane tickets are gathered from the airline´s websites – service aboard, checked-in baggage, or airport check-in. Some of the attributes are defined solely for this thesis: time of the departure is clustered into 3 groups: morning, evening and during-the-day flights. Last feature, business-traveller (BT) route and leisure-traveller (LT) route, was introduced in the previous section.

3.3. Fares development – descriptive evidence

The development of fares is introduced in this section. By observing the development curves, some phenomena might be detected better.

The development of observed fares over time is different for the given routes. On Prague-Brussels (PB) and Brussels-Prague (BP) the prices are stable until the period around 17th day before departure. After that, the fares increase overall mildly – the maximum price increase climbs to 332% above its average. Otherwise, the fares range between 14% above its average to 184% above its average. Only exception is the second evening flight which is sold out and it is very likely that the Czech airlines use the advantage of exceed demand, the systems or managers detect the temporary demand peak and rise the fare.

The question is whether such an increase is dynamic price discrimination or dynamic PLP. The price discrimination uses the customer's higher willingness to pay to rise the fares, whereas the dynamic (or stochastic) PLP is justified by the costs of not-occupied seats. Unfortunately, this is not possible to determine since the cost is unknown. This price-setting change is very likely exhibition of yield management because it seems to react to other airline´s fares. (see sections 2.2 and 2.3Demand uncertainty and capacity utilization). This situation occurs even on the next route.

The fare progress of Prague-Venice (PV) and Venice-Prague (VP) connections is different in the directions. EasyJet sticks to the dominant strategy of LCC - to keep the prices low and increase some weeks before departure - on both directions (Malighetti, et al., 2009). Though, it seems that the other 2 carriers use dynamic PLP method (see section 2.2Peak-load pricing) for setting the price: on VP route, the demand probably stays constant as well as the prices; on the opposite direction, the graph suggests that airlines at first react to higher demand, then the Czech airlines return to original price as demand drops. Here is the possible explanation: the deflection in fares is caused by the fact that Smart Wings include checked-in baggage to every type of a ticket and passengers find that attractive, considering the flight departures at the beginning of summer and the leisure passengers might plan to stay longer. Once Smart Wings sell out their tickets, Czech airlines gather the rest of demand resulting in higher fares.

With no doubt, the development of ticket prices on Berlin-Madrid (BM) and on opposite Madrid-Berlin (MB) route is a bit more chaotic due to numerous carriers. The fares on BM route in simple words are: the Ryanair sets the prices around 1000 CZK which is low and consistent with observations of Ryanair fares in academic research (Malighetti, et al., 2009). The rest of carriers on that route starts with fares 6-times higher than Ryanair and keep it that way. During last 20 days before the day of departure the tickets of all flights except one of the Ryanair's are sold for 3000 CZK. Very likely the prices set at the beginning did not meet the demand. The fare of the only exception on this BM route increases during last 20 days from 1000 CZK to almost 7000 CZK (200% of its average price) and despite such a growth, the tickets are sold out few days before departure. The explanation can be found in times of the flights; the sold-out flight is the single flight operated in the evening.

Among the overall growth of the fares on MB route, some sharp fluctuations can be observed. The first one-day jump should be marked as outlier (z-score equals to 2.75) and most probably this price is an error in the system. However, the next 2 waves might be connected again with the day in the week. It seems that around the weekends the fares are much higher. If those fluctuations are caused by increased demand then it is inconsistent with the assumption that this route is the BT route. The business men are likely to buy the ticket during the week. The last price fall (by 35% of its original value) happens exactly one week before the departure. Capacity utilization and competition of airlines might provide suitable explanation. In order to fill the plane and the seats, one of the carriers, it cannot be recognized which one, lowered temporarily the price. The competitors on the market followed.

On Berlin-Tenerife (BT) and Tenerife-Berlin (TB) route the Ryanair's fares develop independently to some extent. Though, Niki as a subsidiary of AirBerlin, code-share the flight with its parent organization and Niki adopt very similar price schemes, as the graphs suggest[2]. The PD is very low on those routes, minimum fares range between 8% to 51% of average and maximum between 16% and 157% of average. Again, the data collected show that the increase of one of the flight's fares is because of the seats on the other plane are sold out, as it was discussed for the Prague-Brussels route.

All the routes represent various strategies or yield managements of the carriers. However, when compared to the findings from 2013 of Piga and Bachis (2006), the fares collected in 2017 change with greater dynamics. Piga and Bachis present on their graphs that fares are mostly stable until the 2 weeks to departure. Only 2 weeks to departure the fares increase in the majority of cases, which is consistent with the findings described above.

[2] The practice of sharing one aircraft among more airlines which do not need to be necessarily subsidiaries or part of an alliance is very common. In the data set, 12 flights connections are offered by more than 1 airline. Nevertheless, due to anti-trust policies the coordination of pricing strategies among competitors is not allowed, even though some airlines alliances gained the exception (Ratliff & Weatherford, 2013). Due to different orientation of the topic of this thesis, the independent pricing models are assumed.

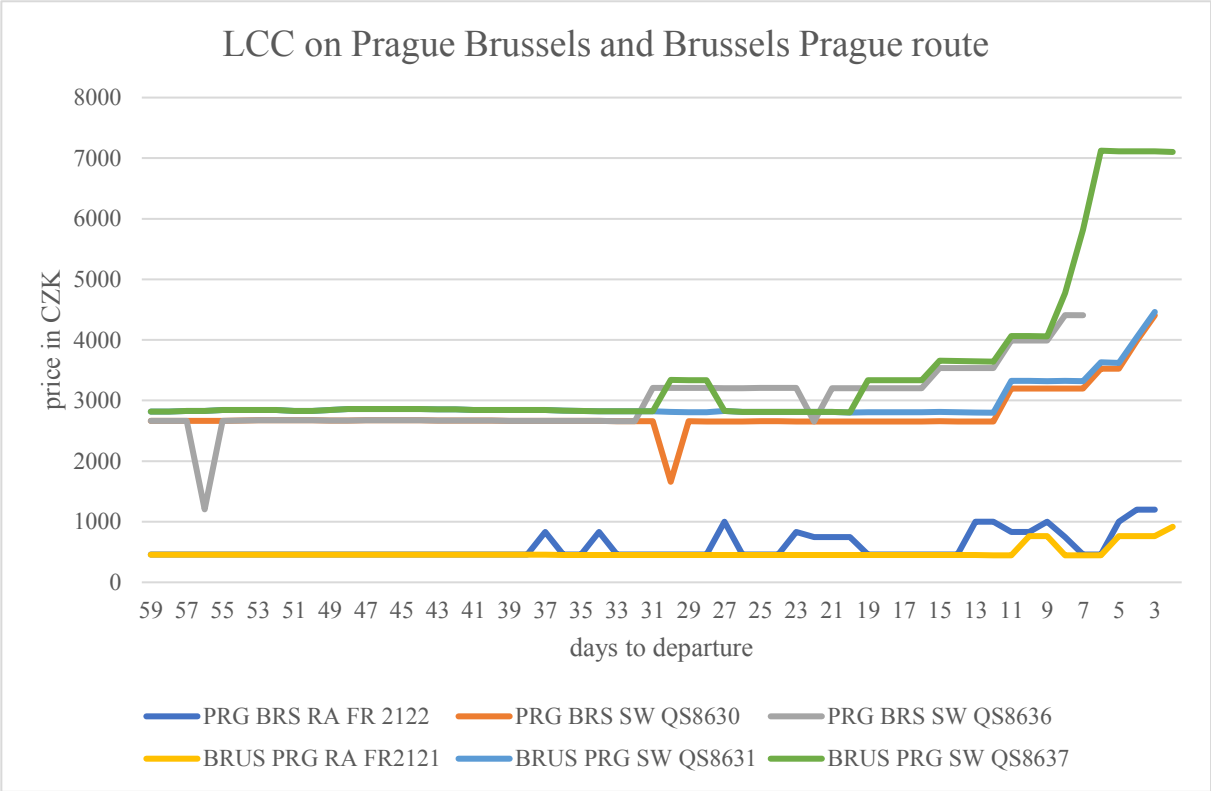

TABLE 5 - example of price development

Some basic descriptive statistic of fares on different routes is designed above. But comparison between LCC and FSC is what may be more interesting. The average change in weekly prices on all routes but gathered into 2 groups might show more about price-setting strategies. Some limitations of small data set can be recognized here, but the fluctuation of FSC prices seem to be a bit more distinct. Secondly, some marks of stable growth of the fares among LCC during the last month before departure can be seen.

DTD	*ΔP-LCC*	*ΔP-FSC*
56	-	-
49	4%	-2%
42	2%	37%
35	19%	1%
28	-7%	-9%
21	31%	-9%
14	32%	18%
7	32%	19%

TABLE 6 – change of the fares of LCC and FSC between presented days to departure (DTD)

3.4. Dependent variable

To find out what affects the price dispersion of plane tickets price, it is crucial to define a measure of PD. In the latest literature, the researchers as dependent variable often choose the Gini coefficient (Gaggero & Piga, 2011), power divergence statistics (Mantin & Koo, 2009), or coefficient of variation which is adopted by this thesis, too (Alderighi, 2010). It must be stated here, that power divergence statistics (PDS) better captures the dynamic nature of price dispersion. However, the attributes of the data used for this thesis do not allow to employ this measure of dispersion. The Gini index is not suitable either, this measure requires larger and richer data set. As Gaggero and Piga (2011) stated: "A possible disadvantage of the Gini coefficient is its large emphasis on the middle part of the distribution and its insensitivity towards the tails of the distribution." It this thesis the focus is aimed mainly to the variations around the middle part of the distributions.

$$CV = \sqrt{\frac{\sum_{i=1}^{n}(p_i - \overline{p})^2}{n-1}} \Big/ \overline{p} = \frac{sample\ standard\ deviation}{sample\ mean}$$

Where $\overline{p} = \frac{\sum_{i=1}^{n} p_i}{n}$.

FIGURE 1 – formula for CV calculation

The coefficient of variation is counted for each flight across fare histories where p_i is the price of ith observation, the prices have been collected every day for 59 days.

The dependent variable is counted for each week and before departure and for each flight in the data set. This frequency is used by Mantin (2009), although he uses different measure of PD. Yet, the weekly frequency will be useful when coping with the load factor and when determining the key determinants of price dispersion.

The summary of dependent variable split into the weeks is presented in Table 7. The first cell contains summary of the coefficient using *dataL* and the cell below is filled with summary created with *dataC*. The coefficients are marked with range of the days; the number of the days decrease as the departure nears, so CV2_8 is the last week to departure. Except the last week, CV2_8, the mean is higher than median, the price dispersion is driven by few flights with high CV during given week.

From the table, it can be registered that PD is greater as the departure approaches and that some 7 or 8 weeks before departure the prises are rather stable. The limitations of the data are noticeable in the table. The *dataL* misses the last week of observations which restrains the following empirical work.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
CV9_15	0.0000000	0.055640	0.096260	0.14160	0.20110	0.5062
CV16_22	0.0002669	0.035330	0.085630	0.14590	0.23530	0.5551
CV23_29	0.0007287	0.002561	0.062930	0.11440	0.17630	0.5070
CV30_36	0.0006705	0.002378	0.050700	0.06217	0.10430	0.2732
CV37_43	0.0003136	0.001874	0.002925	0.06870	0.14290	0.3965
CV44_50	0.0000000	0.002184	0.004331	0.07262	0.10030	0.5748
CV51_57	0.0000000	0.002023	0.003497	0.04984	0.07459	0.3120

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
CV2_8	0.0019550	0.068770	0.164800	0.16330	0.21680	0.4692
CV9_15	0.0000000	0.056330	0.100600	0.14210	0.19700	0.5062
CV16_22	0.0002669	0.039600	0.096040	0.14650	0.23390	0.5169
CV23_29	0.0007287	0.002561	0.063270	0.11560	0.16010	0.5070
CV30_36	0.0006705	0.002378	0.056570	0.06763	0.10760	0.2732
CV37_43	0.0003136	0.001874	0.002930	0.07220	0.14710	0.3965
CV44_50	0.0000000	0.002184	0.002795	0.06409	0.09105	0.5748
CV51_57	0.0000000	0.001948	0.003639	0.04854	0.07353	0.3120

TABLE 7 – summary of the dependent variable

3.5. Independent variables

Route characteristics

POPo/POPd – one of the variable is the population size in the origin/destination area. To keep the measure consistent among the cities and with the existing EU literature, NUTS3 classification of an area is employed.[3] The data set is supplied with values of population measurement from 2016 and the values are in millions on inhabitants. These variables might measure the potential size of market. The more inhabitants certain area around have, the more seats in a plane can be sold. In case of this variable, the area is defined by NUTS3[4] legislation.

[3] http://appsso.eurostat.ec.europa.eu/nui

[4] A common statistical classification of territorial units, hereinafter referred to as 'NUTS' is established in order to enable the collection, compilation and dissemination of harmonised regional statistics. (European Parliament and the Council, 2003)

GDPo/GDPd – other variable is GDP in NUTS3 area of destination/origin in current prices from 2014 in billions of EUR. Again, the GDP in NUTS3 can determine size of a market. If the GDP is driven by the trade and business the flights would be occupied mainly by business travellers and if the GDP is based on services and is seasonal then the flights to such destination are filled with leisure travellers.

Business/Leisure route – separating the routes according to the prevailing type of the customers. It is assumed that price-setting strategies of airlines companies reflect the heterogeneity of the demand size. Dividing the routes according to type of travellers who differ in their price sensitivity is not unusual (Gaggero & Piga, 2011). The data about passenger purpose of travelling can be obtained from UK or US offices, other centralized systems do not exist. The description of how this variable is defined can be found in 3.1.

Flight characteristics

FSC/LCC – a dummy variable distinguishing between 2 primary types of airlines. According to an existing research, the LCC plays role of a competitor to FSC and competes mainly by price cuts. Also, the pricing strategy differs among the LCC and FSC which affects the price dispersion (Giaume & Guillou, 2004). In the paper written by Mantin and Koo, from which this work draws, the LCC dummy is used differently; the authors are interested whether LCC market share affects the PD and overall price level. Here, however, the question is if LCCs fares vary more than FSCs fares.

evening, morning, during – the 3 types of dummies marking the departure time of a flight, the morning dummy marks flights with departure in the time of 6 a.m. to noon, during the day flights have departure between noon and 6 p.m. and evening flights are defined with departure later than 6 p.m. Variables determining the time of departure are important from the consumer point of view. Some departure time might be prioritized and that would cause greater demand and subsequently higher price if the airlines adopt dynamic PLP or even price discrimination.

QualityS – quality of the service provided by the airlines that is included in the price of the ticket. The quality is based on the following included services: check-in at the airport, checked baggage, number of pieces of carry-on luggage (1 or 2), meal and drink aboard. The values are computed as a ratio of the above services provided divided by all the service included. The quality of services might have an impact to changes in prices, indirectly it reveals consumer preferences.

Market characteristics

HHI - Herfindahl-Hirschman index measures market concentration. The higher is the index the more concentrated the market is, i.e. is more monopolistic. HHI index equals to the sum of squared market shares of all firms in given market. It takes shares in percentage form but as an integer. This variable accounts for overall concentration of market. This index might be called the route HHI as the market concentration is measured within one market which is defined as one direction of one route. Each market share is defined as the ratio of the number of flights operated by a given airline in a given route in given month over the total number of flights for all the airlines in a given route in given month. A positive sign of route HHI supports the monopoly effect, while a negative sign is evidence of the brand effect. (Gaggero & Piga, 2011).

airlmarks – ratio expressing number of flights operated by an airline on a route over the total number of flights on that route. The effect of market share of one airline to its set prices should be reflected in this variable. The positive sign supports monopoly effect, i.e. the higher market share, the higher variability of prices.

According to existing research one of the significant variable which affects the PD heavily is load factor. Load factor expresses number of the seats in a plane that has been sold to a given date preceding the date of departure of a particular flight (Belobaba, 2009). However, data set containing the load factor (LF) is difficult to obtain as such data set is not publicly available. The load factor is considered one of the main variable correlated with intra-temporal PD in literature (Belobaba, 2009). And if it is not possible to include this variable into the estimation, some other variable needs to represent it. Suitable proxy for the LF might be price change. The articles which inspect the connection between LF and the price change are, luckily, consistent in the estimates, even across the US and EU aviation market. The relationship is negative, so if price of the ticket decreases the LF increases more than it has been expected without price change – if the load factor is linear function, the slope increases with decrease of price and the effect is immediate in terms of weeks (Escobari, 2012); (Bilotkach, et al., 2015). So, the last variable to comment is price increase.

$Pricei_t$ – change in the fares within one week, the time period is marked with t. This variable is created from the price change within the time period where only positive values

are kept. Overall price increase within one week relates to diminishing load factor. When the demand for given flight is low and the load factor is low as well (number of sold seats is not high enough) the fares are reduced. Only then the very price-sensitive passengers are addressed. As the development of the fares inspection showed (see section 3.3 and Appendix 1)3.3 the prices mostly rise, so the airlines operate with mostly high demand and they do not need to promote sales. For better illustration of the fares development, see Appendix 1. Table 8 summarize the price increase variable.

Price increase - dataC					
Statistic	N	Mean	St. Dev.	Min	Max
priceiw1	31	0.363	0.426	0.000	1.644
priceiw2	31	0.386	0.573	0.000	1.992
priceiw3	31	0.169	0.347	0.000	1.417
priceiw4	31	0.069	0.193	0.000	0.806
priceiw5	31	0.066	0.098	0.000	0.362
priceiw6	31	0.187	0.401	0.000	1.379
priceiw7	31	0.063	0.158	0.000	0.772
priceiw8	31	0.086	0.192	0.000	0.856

Price increase - dataL					
Statistic	N	Mean	St. Dev.	Min	Max
priceiw2	38	0.387	0.561	0.000	1.992
priceiw3	38	0.223	0.568	0.000	3.046
priceiw4	38	0.057	0.176	0.000	0.806
priceiw5	38	0.070	0.099	0.000	0.362
priceiw6	38	0.184	0.380	0.000	1.379
priceiw7	38	0.098	0.217	0.000	0.772
priceiw8	38	0.074	0.176	0.000	0.856

TABLE 8 – summary of the price increase - explanatory variable

The estimations are based on 2 types of data set from which the CV is counted, because of missing data. The first one, called *dataC*, omits every flight with non-complete price development and the second, called *dataL* omits last 5 observations and 2 flights more because of missed observations. The final data set contains either 38 flights with 53 recorded prices (frequency is every day) or 31 flights with 58 recorded prices. The inspection of the model 1 (Figure 2) and model 2 (Figure 3) is done with *dataC*; data is split to weeks then the same procedure is repeated with *dataL*. Further, the variables that might affect the PC are inspected. At the end, the effect of outliers is discussed.

4. Model

The goal of this thesis is to find the key determinants of the plane tickets intra-temporal price dispersion measured by CV. It is obvious that this is not the first attempt to find out, so the task is to build on previous research. The idea is to find out the crucial determinants of the PD and whether specific characteristics of the flight and market structure have any effect. Finally, what might be interesting, due to fast-changing environment of European civil aviation market, to what extent the LCC change PD in comparison to FSC. So, the aim is to determine if route, flight, and market specifications have an impact to CV and the size of the impact. Some very marginal features of the flights will be, after the first examination of the model, incorporated into the econometric model; it is assumed that some of them or the interaction effects might be significant.

The model is based on the theory that PD is affected by market structure qualities, size of potential market power and specification of the flight which, apart from the price, are important for the customers. (Gaggero & Piga, 2011); (Mantin & Koo, 2009). This model is inspected carefully and then some other characteristics and their interactions will be included in the model.

$$CV_t = \beta_0 + \beta_1 LCC + \beta_2 HHI + \beta_3 GDPo + \beta_4 GDPd + \beta_5 evening + \beta_6 morning + \beta_7 pricei_t$$

FIGURE 2 – estimated model 1

The stability of the results is inspected using model where the GDP is replaced with population variables. The GDP variables have similar justification to be in the model as population of the destination and origin; both variables reflect the effect of the potential size of the market. In the following part, the GDPo and GDPd are switched with POPo and POPd:

$$CV_t = \beta_0 + \beta_1 LCC + \beta_2 HHI + \beta_3 POPo + \beta_4 POPd + \beta_5 evening + \beta_6 morning + \beta_7 pricei_t$$

FIGURE 3 – estimated model 2

The outlier robust estimation closes the inspection of the model 1. Outlier robust estimation is chosen, since the limitations of the data set do not allow to choose the easy procedure how to avoid its side effects– omitting the observations with such values. Better approach is to lower the undesirable influence in the estimation. Such estimation method is called M-estimation. The name follows the principle of maximum-likelihood estimation (Fox & Weisberg, 2010). This method down-weights outliers according to how far they are from the best-fit line.

5. Results

Results with *dataC*

The first estimation shows none of the variable is significant for all 8 weeks and the power of those variables to explain the changes in CV varies. The residual standard error ranges between 0.042 to 0.112. All the results from model 1 using *dataC* are presented in Appendix 2.

Some interesting results are that for the first month of the observations (out of 2) the LCC is significant positive dummy. The low-cost airlines change the price more heavily than the traditional ones during that month approx. by 0. 055 on average, the coefficients are always positive. This difference in pricing policy may be effect of a demand-sensitive software or setting that define the prices. As the LCCs focus on the price-sensitive customers, they seem to reflect the level of demand in prices immediately. In other words, LCCs probably use more dynamic PLP than FSCs. This result is not supported by the literature which claims that LCC's prices stay low and increase heavily during the last 2, or 3 weeks prior departure (Piga & Bachis, 2006). Market structure, measured in HHI, is significant only the last week before the departure, otherwise the effect of route market concentration to the size of CV is zero. Only the last week to departure positively contributes to the variation of the fares. This supports the monopoly effect on the price dispersion only slightly since the economic impact is very low. On the other hand, the GDP of the origin is significant in 6 estimations, however, without any pattern among the weeks before departure and without large economic importance. The estimated coefficients are low (0.0003 – 0.0004) at the beginning of the observation period and grows by one order (0.001- 0.002). The GDP variable is in billions of EUR. Such a change in GDP is not very likely but if such increase happened, the change in the response

variable CV would be marginal. So implicitly, even though the size of the market is significant, the importance to CV of fares is very low.

Evening and morning flights have significant impact to CV as the departure nears, however the direction of the effect changes. Between week3 and week5 prior to departure, the morning and evening flights have the CV higher up to 0.101 points and last week to departure the prices stabilize in comparison to the during-the-day flights (up to -0.095 points). The airlines probably try to attract the consumers with fast sales to fill the plane and increase the certainty of full plane. Or from the other side, the airlines reflect the number of arranged and cancelled bookings. During week1 the fares of the during-the-day flight prices vary as the morning and evening dummies decrease the CV.

The increase of price is significant and with large effect.

The model is tested for joint significance of 2 pairs of variables: morning and evening, GDPo and GDPd. The test for morning and evening pair shows similar significant pattern that is discussed above, the pair is significant maximally on 10% significance level in the week1, 2, 3, and in week6; the lower number of the week, the closer to the departure. So, during the other weeks these dummies have zero effect on CV. The absolute values of the morning and evening flights fares reveal that the prices of all the flights are high at the end of sale. This result, when combined with the positive significant effect of price increase, might be a prove of the hypothesis that late customers care about the time. In detail: late customers mainly business-men are time-sensitive and search for some suited time of the departure. Airlines rely on it and keep the prices high. The joint significance of GDP variables is overall very significant. Both, GDP of the origin and of the destination, are relevant for the variation of fares among the weeks.

The second model, as demonstrated in Figure 3, is described in the following paragraph. The table of results is presented in Appendix 4. The estimation is corrected for heteroscedasticity as well. When comparing the model with GDPs (Figure 2) and POPs (Figure 3) using the $\overline{R^2}$, the second model in majority better describes the variation in CV. Possibly the model 2 just better suits the data, or the model with population is closer to the true model. The stability of the estimates in the model is unexpectedly high – the significance and directions does not change and the values of the estimates themselves

differ only in thousandths. Obviously, the estimates of populations are not the same, as the unit is different, the significant ones are positive and they vary between 0.008 and 0.056. The population is measured in millions of inhabitants so if number of the residents in NUTS3 area increases by 1 million the CV of fares during specific weeks before the departure increases. But potential pitfall of larger surrounding population is its uneven distribution of preferred flights and times. As the potential number of passengers rise, the uncertainty of demand grows too (Escobari & Lee, 2014). Despite the growth of the market potential, the volatility of demand is higher, which is not desirable for the airlines (see section 2.2).

Results with *dataL*

The *dataL* data set consists of observations without last 5 days because many observations are not complete in this period. Moreover, 3 flights must be deleted since they suffered from lack of values. *DataL* has the advantage in the form of more flights but also disadvantage, it loses the observations of last week before the departure. It is unfortunate because the week closest to the departure is the one most interesting. However, still the data set is useful for comparison of the results.

The results are already presented with heteroscedastic robust SE in Appendix 3. The first examination reveals that none of the weekly regressions provide the same set of significant variables. The estimations based on different data are similar in explaining the variance of CV - $\overline{R^2}$ of the estimations differ just a little, which is important, since it shows robustness of the previous results.

Specifically, low-cost carriers are even more significant and still positive with the range of 0.35 – 062 during the first month. The estimates are a bit lower but still have large economic impact. The GDP of the origin is significant across weeks without pattern. The differences are notable during week7 and 8 where the GDP of origin is much less significant. The variables representing market size (GDP and population) are not very consistently significant during week7 and 8. However, the GDP of the origin is more often significant than GDP of the destination, i.e. the CV of fares is determined by the market size of origin. The estimates of morning and evening dummies differ a bit, as the sample data change between *dataL* and *dataC.* All the price increases are highly significant and positive proving the load factor causes more dispersed prices.

Morning and evening variables are jointly significant on 5% level once at week3 and on 10% level at week6. Those dummies affect the CV of price only sometimes but consistently across the data sets. The GDP of the origin and the destination are jointly significant at week3, 4, 6, and 8.

Estimating model 2 with *dataL* shows, that model 2 is slightly better when comparing adjusted R^2, again. The results prove high stability of estimates of LCC. The HHI index becomes insignificant, which raises the question, whether this variable should be in the model 2. The market concertation plays a role only in week1 when using *dataC*. The population of the origin is highly significant which is consistent with previous POP and GDP results. The rest of the findings are overall similar to those with *dataC*, that implies quite robust results. Table of results is again shown in Appendix 5.

All the models above are tested for violation of the assumptions of the OLS model. The homoscedasticity of standard errors is tested with Breusch-Pagan test. The null hypothesis of homoscedasticity is rejected on 5% significance level for some estimations. But to make the results comparable, all the results of OLS discussed above and presented in Appendix 2 use heteroscedastic robust SE. The multicollinearity is checked with graphical representation. The evidence of functional form misspecification is found for week4 for both data sets using RESET test and significance level of 1%. Still, the goal is to compare the results between each other so the model is not treated.

The results reveal how differences of fares are driven by diverse factors, mainly by price increase. Surely, the correlation between CV and price increase is always present and always positive. But the price increase represents the diminishing load factor: the larger price increase, the lower the load factor. Some academic papers mention that load factor may be negative due to the cancelled flights. This phenomenon is, however, very marginal and is not accounted for it. The fares are influenced by GDP or population and market structure to a small extent, although they are very statistically significant. The features of the flights and airlines have larger impact to the CV of fares. It can be argued what is the causality of these relationships. In the following subsection, additional characteristics are tested for significance.

Additional variables and interaction terms

As addressed several times throughout the thesis, the aim is to discover if additional variables which describe airline characteristics affect the price dispersion. In the following subsection, the model, as illustrated in Figure 2 is supplemented with variables described in the section 3.5 that has not been used so far.

The variables tested for significance using t-tests are: airline market share, quality of the service included in the price of the tickets, interaction of LCC and leisure route, and interaction of FSC and business route. Those interactions will check different pricing of LCC and FSC on different routes.

The airline market share is significant and negative on 10% significance level only 1 week to departure, the estimate is large in absolute value and is interpreted as follows: increase of market share by 10% results in 0.036 decrease of CV. At the end of the sale, the airlines with higher market share set more stable fares. The value and significance of the other variable from the model are basically unaffected. Sadly, those results cannot be confirmed with the second data set, since it does not contain data for week1.

The quality is insignificant for CV of fares in all weeks except the week3 to departure – the estimate is negative, which is consistent across both data sets. In this week, the higher-quality flights provide less dispersed fares.

The LCC and leisure route interaction is negative 2 weeks prior to departure and positive during week3. The flights operated by LCC on leisure routes have less dispersed prices at the end of the sales and more dispersed in week3 to departure. Price sensitive leisure passengers are behind this phenomenon as they typically buy the tickets in advance. The LCC face the brunt of leisure consumers during that week3 when the fares are dispersed more. The interaction effect of LCC and leisure route decreases the significance of GDPo in 3 consecutive weeks the farthest from the departure, increases the significance of LCC in the week1- the closest to departure - and deviates the value of many estimators marginally. The test for multicollinearity reveals negative correlation between LCC*l interaction term and both GPD variables. The leisure routes (either operated by FSC or LCC) are less inhabited in the destinations, given those data sets. The results are similar using *dataC* or *dataL*.

Interaction of business route and FSC is significant and highly negative last week to departure. When comparing this result with graphs in Appendix 1 it becomes clear that

FSC just set the prices high. It is assumed that late price-insensitive passengers buy the tickets anyway. Of course, LCC is taken a lot of effect to CV by the interaction term. Test for multicollinearity shows almost perfect negative correlation. However, other estimators stay unchanged.

The table of results from this subsection is presented in the Appendix 8 to Appendix 11.

Results with outlier robust estimation

One possible defect has not been corrected yet. The influence of outliers. Since the test for outliers show half of the estimations using both *dataL* and *dataC* contain outliers, running the outlier-robust estimations reveal the bias.

The results using *dataC* and outlier robust estimation show the biases are rather medium-sized. The estimators differ within the same order and the significance of estimators is shifted mainly among the usually reported significance levels of 0.001 and 0.01. But some exceptions occur: the morning variable becomes insignificant in week 5 and 6, GDP of the origin and index of market concentration, HHI, turn to be significant. However, the estimate of GDP is small and the situation when GDP starts to be economically important is very unlikely. When comparing results between OLS and M-estimation using *dataL* more estimates change the significance. In week2 GDPo and morning dummy become significant; now the morning flights increase the CV by 0.033 points. In week6, the morning dummy turns insignificant. The table of results is presented in Appendix 6 and Appendix 7.

Overall, the outlying values affect the estimations a bit. It would be surely helpful to have larger data set for more precise results.

6. Conclusion and discussion

This thesis explores plane tickets prices, how they develop during the period of 8 weeks prior departure. The inter-temporal changes in fares are described and the explanations of the fluctuations are based on the theory and existing literature, that is discussed in the first part of the thesis. The fares description provides insight into the different price-setting strategies of examined airlines. Marks of peak-load pricing, demand utilization, and competitive behaviour are found. Those dynamic strategies are accompanied by typical strategy of low-cost airlines; simply keeping the fares low. This description revises the

findings of existing literature. When the results of this thesis are compared to the literature that was published 10 years ago, the findings show that airlines have adopted more dynamic pricing system, that accommodates to the varying demand and its peaks. The empirical part examines the factors influencing the price dispersion of observed fares. Using coefficient of variation, that measures changes in ticket prices within week intervals, enables to define elements that affect the variation in fares. Also, the differences among the weeks can be seen and determined. The model stemming from literature is estimated using data that are collected by the author. The results show evidence that load factor of the given plane is key factor affecting the fares across the weeks. This is determined by the proxy variable that is used instead of lacking data about load factor. The measure of potential market size, either representing by the GDP or size of the population, is another important variable, however with small economic importance. Other variables, such as low-cost carrier dummy, morning and evening dummies marking the time of departing flights, are significant only at some weekends.

Limitation of this thesis is the data set, as it has 3 disadvantages: its small, with missing values and it does not contain the data about load factor. Also, it would be interesting to study the price development of whole sale period. The literature shows that the graphical representation of offered airline fares resembles U-shaped curve. Another approach for studying the differences among factors having an effect on price dispersion is to divide the period of sale into 2 periods classified like “long time to departure” and “close to departure”. The latter is characteristic for more dynamic changes of prices. Then the panel method might be used.

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8. List of figures

9. List of tables

10. List of appendices

11. List of acronyms

business-traveller (BT)

coefficient of variation (CV)

full-service carriers (FSC)

Herfindahl-Hirschman Index (HHI)

International Civil Aviation Organization (ICAO)

leisure-traveller (LT)

load factor (LF)

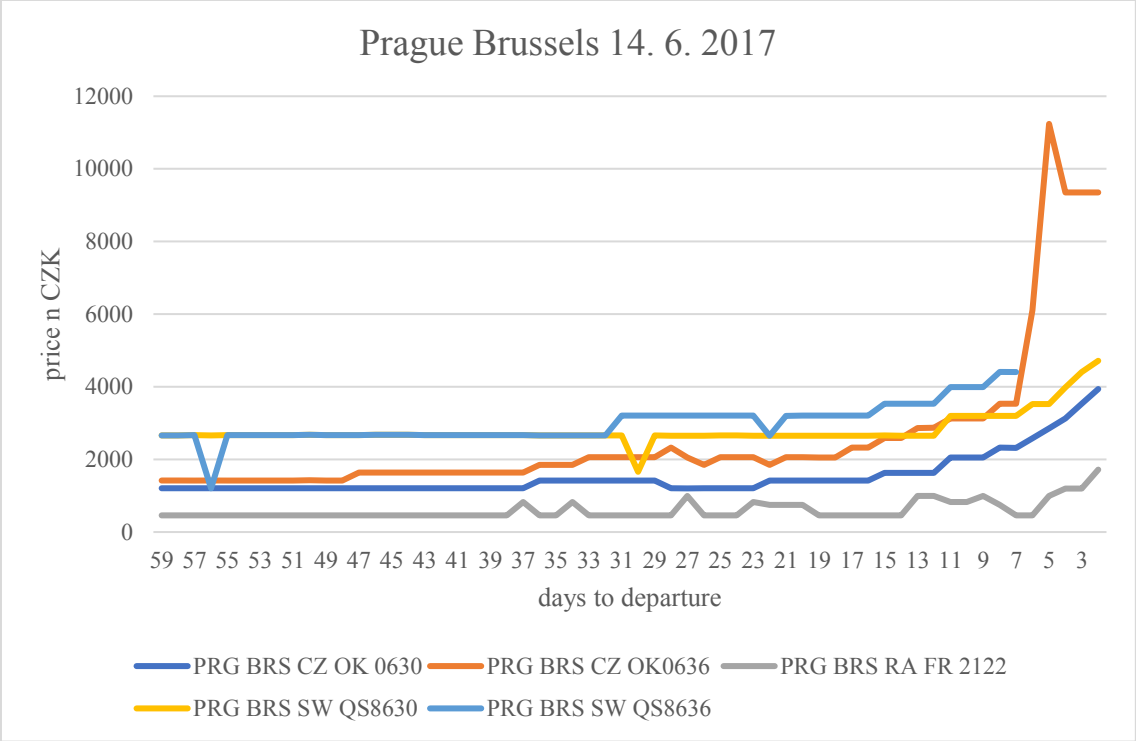
low-cost carriers (LCC)

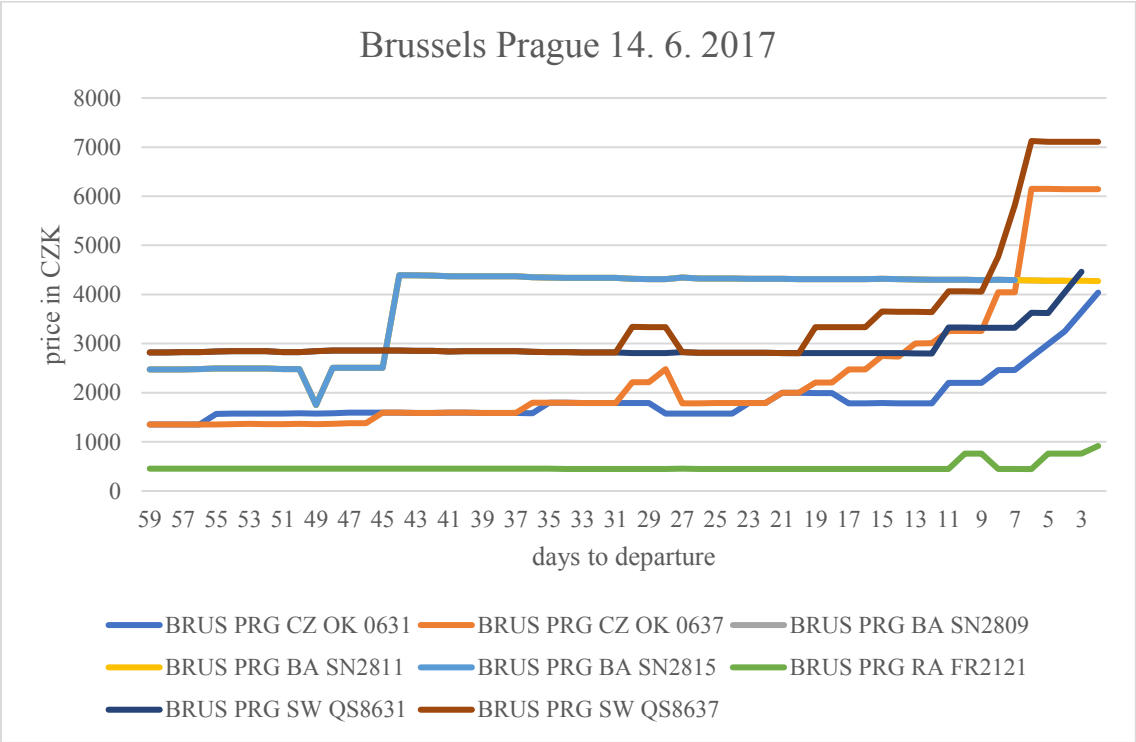
peak-load pricing (PLP)

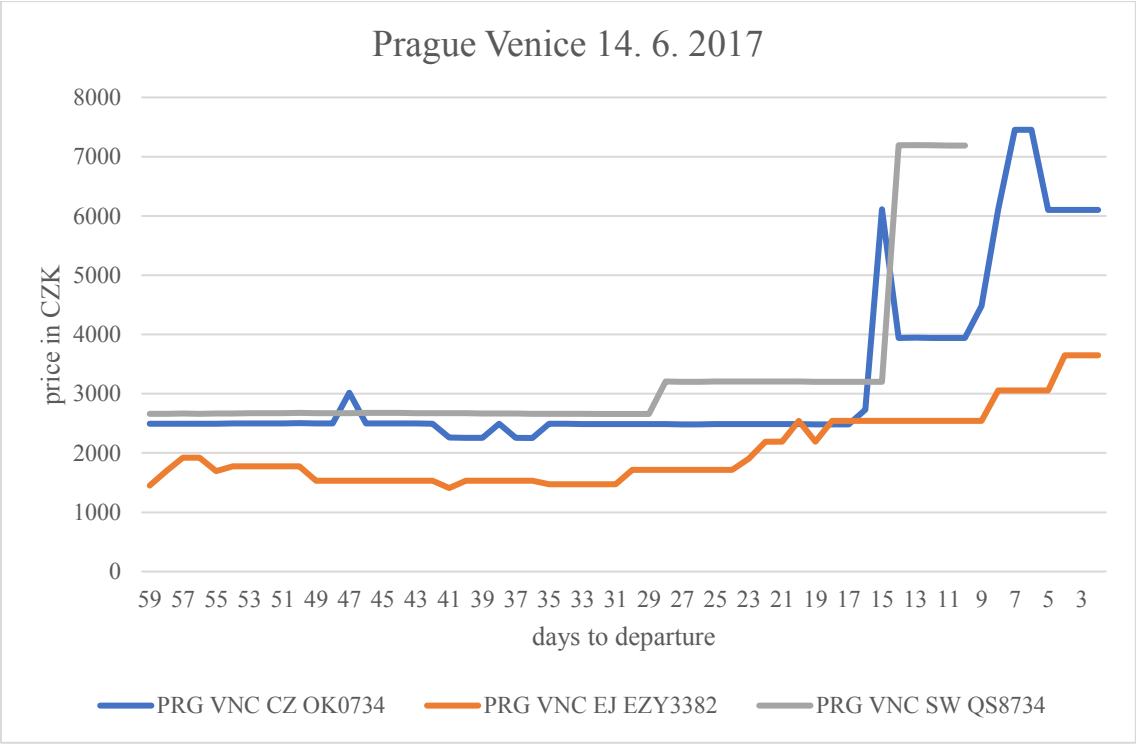
price dispersion (PD)

yield management (YM)

Appendix 1 – Tables of fares on observed routes






Prague Venice 14. 6. 2017
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8000
7000
6000
5000
4000
3000
2000
1000
0
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3
days to departure
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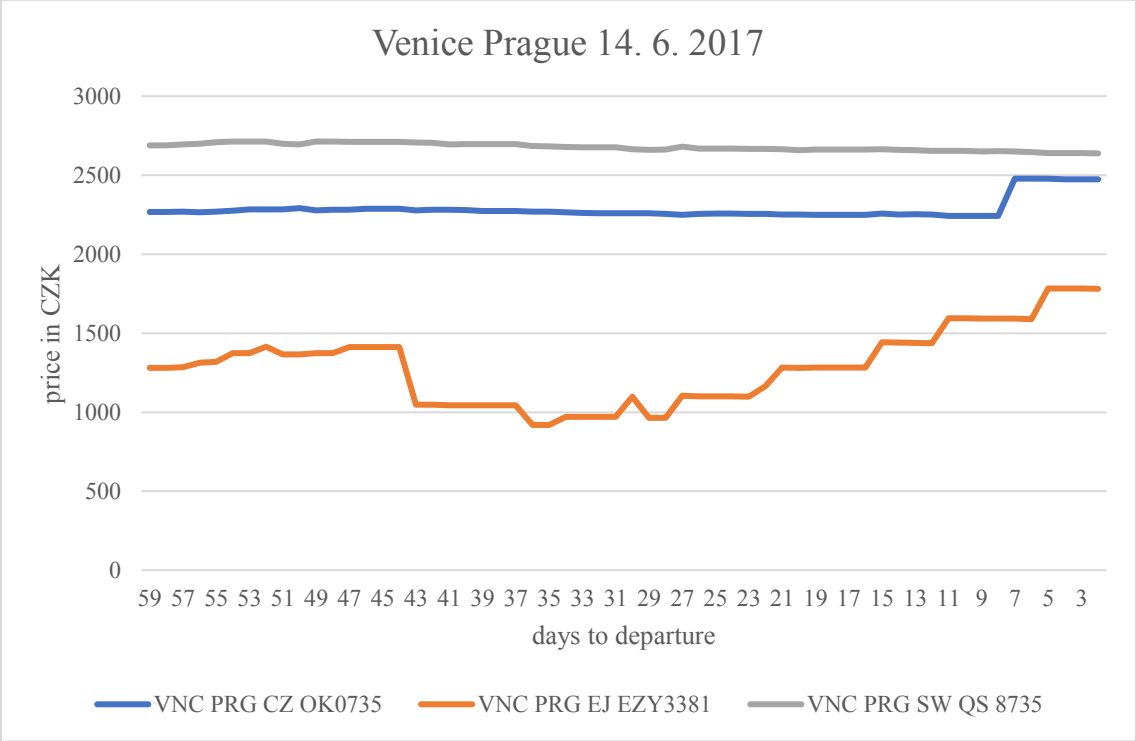
PRG VNC EJ EZY3382
PRG VNC SW QS8734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price in CZK
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2500
2000
1500
1000
500
0
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3
days to departure
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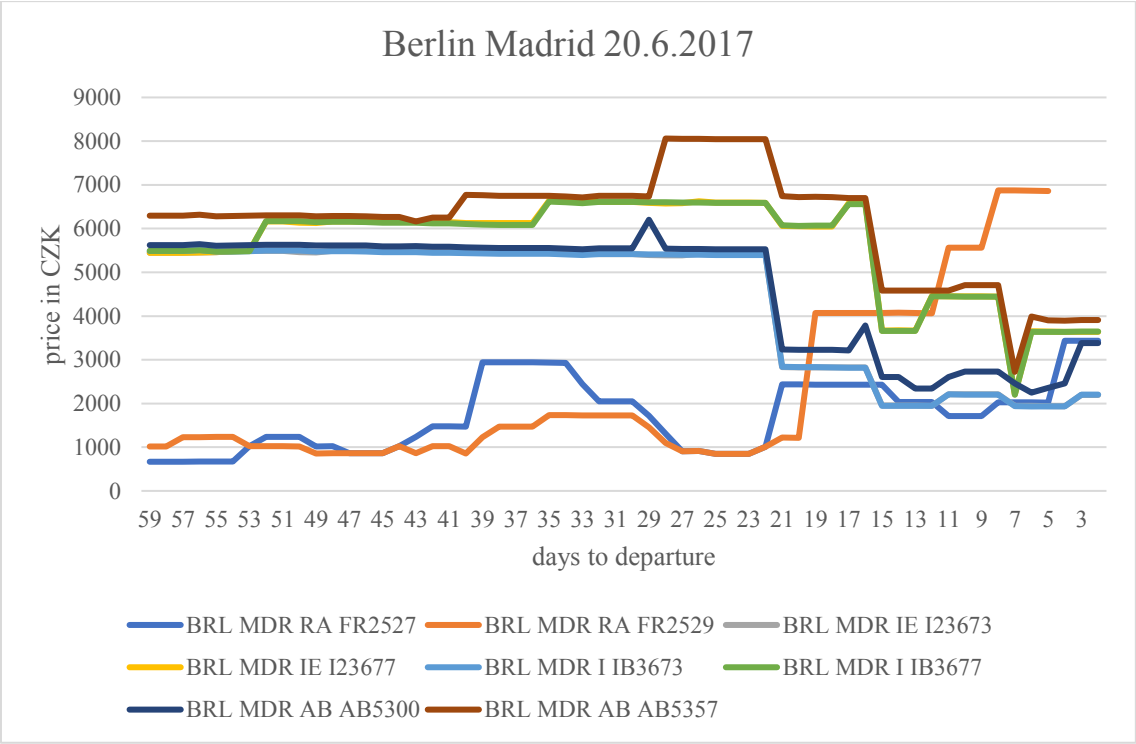
VNC PRG EJ EZY3381
VNC PRG SW QS 8735


Berlin Madrid 20.6.2017
price in CZK
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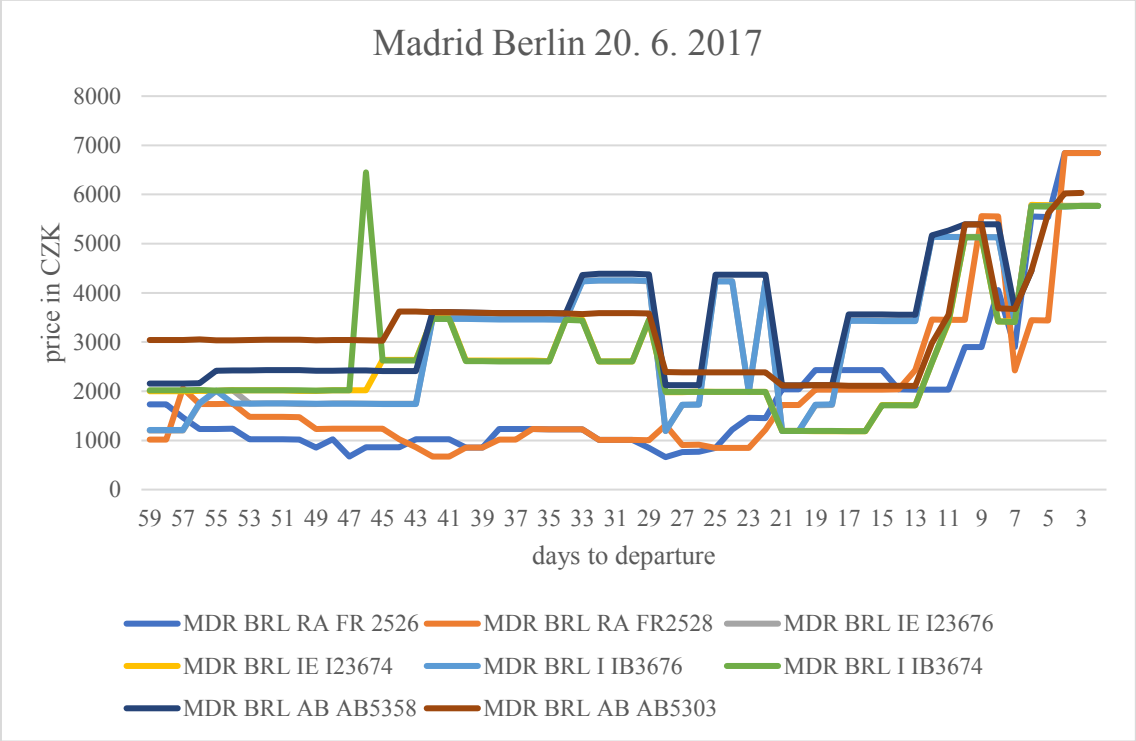
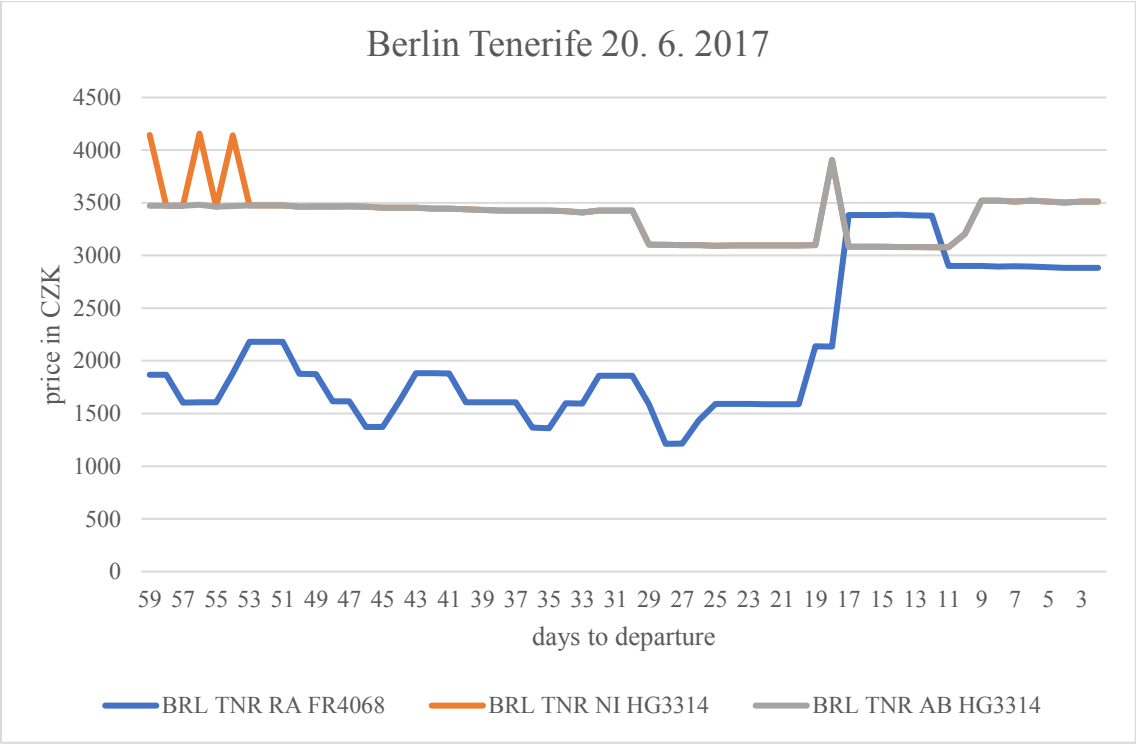
8000
7000
6000
5000
4000
3000
2000
1000
0
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3
days to departure
BRL MDR RA FR2527
BRL MDR RA FR2529
BRL MDR IE I23673
BRL MDR IE I23677
BRL MDR I IB3673
BRL MDR I IB3677
BRL MDR AB AB5300
BRL MDR AB AB5357


Madrid Berlin 20. 6. 2017
price in CZK
8000
7000
6000
5000
4000
3000
2000
1000
0
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3
days to departure
MDR BRL RA FR 2526
MDR BRL RA FR2528
MDR BRL IE I23676
MDR BRL IE I23674
MDR BRL I IB3676
MDR BRL I IB3674
MDR BRL AB AB5358
MDR BRL AB AB5303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4000
3500
3000
2500
2000
1500
1000
500
0
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3
days to departure
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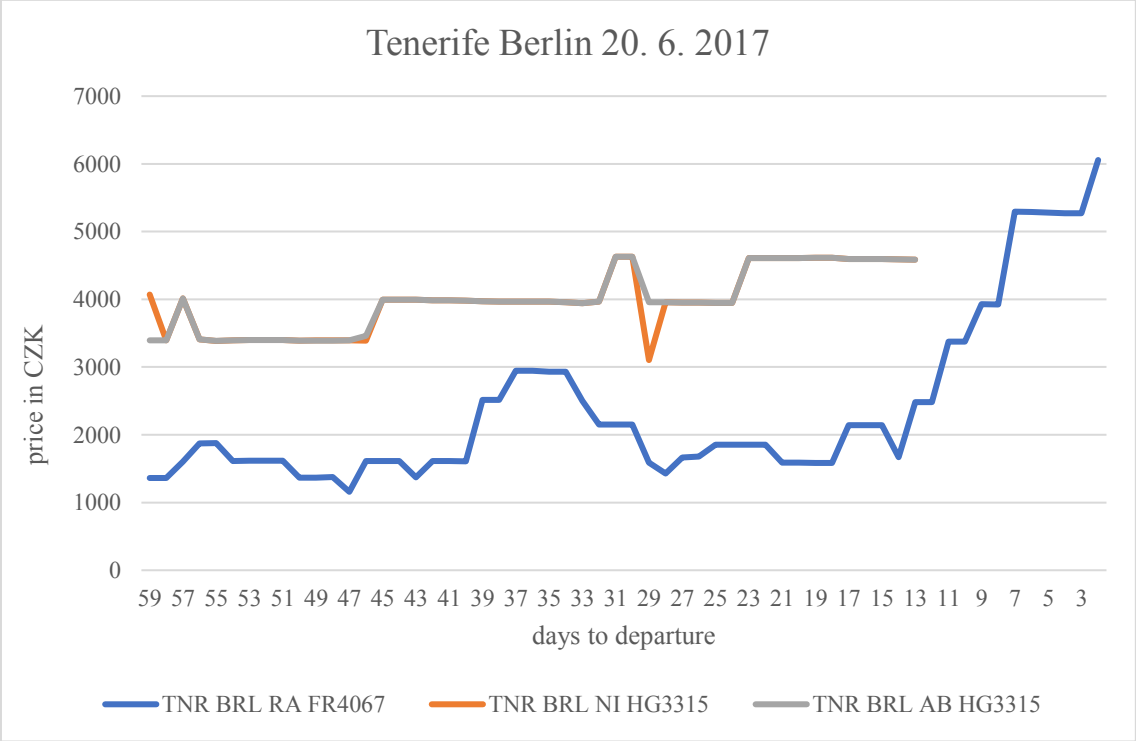
BRL TNR NI HG3314
BRL TNR AB HG3314


Tenerife Berlin 20. 6. 2017
price in CZK
7000
6000
5000
4000
3000
2000
1000
0
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3
days to departure
TNR BRL RA FR4067
TNR BRL NI HG3315
TNR BRL AB HG3315

Appendix 2 – Table of results; model 1; dataC

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	0.012	0.004	-0.026	0.023
	(0.023)	(0.021)	(0.044)	(0.046)
HHI	0.0001	0.00000	-0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP in origin	0.001***	0.0001	0.001***	0.002***
	(0.0002)	(0.0002)	(0.0004)	(0.0005)
GDP in destination	0.0005***	-0.00000	0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0004)
evening flight	-0.095**	-0.004	0.042	0.067**
	(0.035)	(0.030)	(0.031)	(0.031)
morning flight	-0.067**	0.029	0.101***	0.059
	(0.024)	(0.021)	(0.037)	(0.038)
price increase 1	0.269***			
	(0.034)			
price increase 2		0.223***		
		(0.020)		
price increase 3			0.069	
			(0.062)	
price increase 4				0.264**
				(0.132)
intercept	-0.304	0.027	0.307	-0.366
	(0.204)	(0.167)	(0.333)	(0.294)
Observations	31	31	31	31
R2	0.867	0.902	0.529	0.529
Adjusted R2	0.827	0.873	0.386	0.386

Note: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.082***	0.043**	0.051	0.045***
	(0.025)	(0.018)	(0.035)	(0.012)
HHI	0.0001	-0.00002	-0.0001	-0.00005
	(0.0001)	(0.0001)	(0.0001)	(0.00003)
GDP in origin	0.0002	0.0004**	0.001	0.0003**
	(0.0002)	(0.0002)	(0.0003)	(0.0001)
GDP in destination	0.0003	0.0001	0.0001	0.00000
	(0.0002)	(0.0001)	(0.0003)	(0.0001)
evening flight	0.062*	0.030	0.063	-0.011
	(0.036)	(0.024)	(0.048)	(0.013)
morning flight	0.032	-0.022	-0.012	-0.0005
	(0.027)	(0.019)	(0.036)	(0.010)
price increase 5	0.177			
	(0.128)			
price increase 6		0.236***		
		(0.023)		
price increase 7			0.499***	
			(0.110)	
price increase 8				0.276***
				(0.024)
intercept	-0.173	0.020	0.200	0.090
	(0.209)	(0.142)	(0.285)	(0.089)
Observations	31	31	31	31
R2	0.384	0.883	0.611	0.881
Adjusted R2	0.196	0.847	0.493	0.845

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 3 – Table of results; model 1; dataL

	Dependent variable:		
	CV9-15	CV16-22	CV23-29
	(1)	(2)	(3)
LCC	0.011	-0.028	0.025
	(0.016)	(0.046)	(0.041)
HHI	-0.00003	-0.0002	0.00004
	(0.0001)	(0.0001)	(0.0001)
GDP in origin	0.0001	0.001**	0.002***
	(0.0002)	(0.0004)	(0.0004)
GDP in destination	0.0001	0.0002	-0.00004
	(0.0001)	(0.0003)	(0.0003)
evening flight	0.006	0.038	0.061
	(0.023)	(0.055)	(0.054)
morning flight	0.026	0.100**	0.056
	(0.019)	(0.045)	(0.046)
price increase 2	0.227***		
	(0.017)		
price increase 3		0.124***	
		(0.041)	
price increase 4			0.274**
			(0.113)
intercept	0.086	0.393	-0.197
	(0.145)	(0.349)	(0.357)
Observations	38	38	38
R2	0.912	0.600	0.538
Adjusted R2	0.892	0.506	0.430
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
	(1)	(2)	(3)	(4)
LCC	0.060**	0.035**	0.044	0.062***
	(0.022)	(0.015)	(0.030)	(0.015)
HHI	0.00002	-0.00002	-0.0001	-0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP in origin	0.0002	0.0003**	0.0004	0.0002
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
GDP in destination	0.0002	0.00002	0.00003	0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
evening flight	0.027	0.009	0.030	0.018
	(0.030)	(0.020)	(0.038)	(0.021)
morning flight	0.028	-0.022	-0.017	-0.002
	(0.026)	(0.018)	(0.033)	(0.018)
price increase 5	0.171			
	(0.109)			
price increase 6		0.238***		
		(0.022)		
price increase 7			0.453***	
			(0.072)	
price increase 8				0.285***
				(0.044)
intercept	-0.087	0.037	0.213	0.026
	(0.197)	(0.130)	(0.258)	(0.136)
Observations	38	38	38	38
R2	0.291	0.877	0.652	0.724
Adjusted R2	0.125	0.849	0.570	0.659
Note:	*p<0.1; **p<0.05; ***p<0.01			

Appendix 4 – Table of results; model 2; dataC

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	0.012	0.004	-0.033	0.022
	(0.018)	(0.024)	(0.045)	(0.047)
HHI	0.0002***	0.00001	-0.0001	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
POP in origin	0.021***	0.004	0.038***	0.056***
	(0.007)	(0.005)	(0.013)	(0.014)
POP in destination	0.014***	-0.0004	-0.001	-0.010
	(0.003)	(0.005)	(0.011)	(0.012)
evening flight	-0.096***	-0.004	0.034	0.051
	(0.034)	(0.028)	(0.036)	(0.035)
morning flight	-0.065***	0.029	0.099***	0.055
	(0.022)	(0.020)	(0.034)	(0.036)
price increase 1	0.268***			
	(0.026)			
price increase 2		0.221***		
		(0.015)		
price increase 3			0.076	
			(0.062)	
price increase 4				0.218*
				(0.131)
intercept	-0.445**	0.007	0.170	-0.572*
	(0.176)	(0.179)	(0.368)	(0.325)
Observations	31	31	31	31
R2	0.873	0.903	0.550	0.590
Adjusted R2	0.834	0.873	0.414	0.465
Note:		*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.078***	0.041**	0.048**	0.044***
	(0.023)	(0.018)	(0.023)	(0.012)
HHI	0.0001	0.00000	-0.0001	-0.00003
	(0.0001)	(0.00004)	(0.0001)	(0.00004)
POP in origin	0.012**	0.014***	0.019*	0.008**
	(0.006)	(0.005)	(0.010)	(0.004)
POP in destin,	0.003	-0.0001	0.00001	-0.0002
	(0.005)	(0.004)	(0.005)	(0.002)
evening flight	0.052*	0.026	0.058	-0.012
	(0.027)	(0.023)	(0.056)	(0.013)
morning flight	0.029	-0.022**	-0.013	-0.001
	(0.019)	(0.011)	(0.017)	(0.010)
price increase 5	0.144*			
	(0.074)			
price increase 6		0.234***		
		(0.025)		
price increase 7			0.501***	
			(0.095)	
price increase 8				0.278***
				(0.025)
intercept	-0.255	-0.034	0.124	0.067
	(0.244)	(0.110)	(0.138)	(0.094)
Observations	31	31	31	31
R2	0.398	0.890	0.623	0.880
Adjusted R2	0.214	0.857	0.508	0.844
Note:		*p<0.1; **p<0.05; ***p<0.01		

Appendix 5 – Table of results; model 2; dataL

	Dependent variable:		
	CV2-8	CV9-15	CV16-22
LCC	0.011	-0.036	0.026
	(0.018)	(0.037)	(0.033)
HHI	-0.00001	-0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
POP in origin	0.001	0.002	-0.006
	(0.004)	(0.009)	(0.010)
POP in destination	0.005	0.032***	0.054***
	(0.005)	(0.012)	(0.012)
evening flight	0.006	0.028	0.048
	(0.023)	(0.036)	(0.032)
morning flight	0.026	0.099***	0.053
	(0.021)	(0.032)	(0.033)
price increase 2	0.223***		
	(0.013)		
price increase 3		0.133***	
		(0.028)	
price increase 4			0.229*
			(0.132)
intercept	0.051	0.232	-0.439
	(0.167)	(0.300)	(0.288)
Observations	38	38	38
R2	0.913	0.618	0.594
Adjusted R2	0.892	0.529	0.499
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.060***	0.034***	0.044***	0.062***
	(0.019)	(0.012)	(0.016)	(0.017)
HHI	0.0001	-0.00000	-0.0001	-0.00001
	(0.0001)	(0.00004)	(0.00005)	(0.00004)
POP in origin	-0.0001	-0.0005	-0.0002	0.002*
	(0.005)	(0.003)	(0.004)	(0.001)
POP in destin,	0.012**	0.011**	0.015	0.006*
	(0.006)	(0.004)	(0.009)	(0.004)
evening flight	0.020	0.007	0.027	0.016
	(0.020)	(0.017)	(0.035)	(0.020)
morning flight	0.024	-0.022**	-0.017	-0.003
	(0.018)	(0.010)	(0.015)	(0.010)
price increase 5	0.147**			
	(0.071)			
price increase 6		0.236***		
		(0.023)		
price increase 7			0.460***	
			(0.047)	
price increase 8				0.285***
				(0.020)
intercept	-0.164	-0.007	0.152	-0.009
	(0.228)	(0.095)	(0.119)	(0.116)
Observations	38	38	38	38
R2	0.321	0.882	0.658	0.725
Adjusted R2	0.163	0.854	0.578	0.661
Note:	*p<0.1; **p<0.05; ***p<0.01			

Appendix 6 – Table of results; model 1 using RLM; data C

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	-0.002	0.024	-0.018	0.027
	(0.020)	(0.016)	(0.046)	(0.032)
HHI	0.0001**	0.00002	-0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP in origin	0.001***	0.0002	0.001**	0.001***
	(0.0002)	(0.0002)	(0.0004)	(0.0003)
GDP in destination	0.0005***	0.0001	0.0003	-0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0002)
evening flight	-0.083***	0.014	0.064	0.085**
	(0.030)	(0.023)	(0.055)	(0.041)
morning flight	-0.055***	0.038**	0.085**	0.019
	(0.021)	(0.016)	(0.041)	(0.031)
price increase 1	0.252***			
	(0.029)			
price increase 2		0.221***		
		(0.015)		
price increase 3			0.069	
			(0.061)	
price increase 4				0.364***
				(0.077)
intercept	-0.312*	-0.053	0.355	-0.242
	(0.174)	(0.131)	(0.323)	(0.248)
Observations	31	31	31	31

Note: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.056***	0.040**	0.042**	0.036***
	(0.009)	(0.018)	(0.018)	(0.010)
HHI	0.0001**	-0.00001	-0.0001	-0.0001*
	(0.00003)	(0.0001)	(0.0001)	(0.00003)
GDP in origin	0.0005***	0.0004***	0.0003*	0.0002*
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
GDP in dest.	0.00001	0.00003	0.00001	-0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
evening flight	0.043***	0.026	0.007	-0.007
	(0.013)	(0.024)	(0.025)	(0.014)
morning flight	0.007	-0.021	-0.013	0.001
	(0.010)	(0.020)	(0.019)	(0.011)
price increase 5	0.225***			
	(0.047)			
price increase 6		0.245***		
		(0.024)		
price increase 7			0.418***	
			(0.056)	
price increase 8				0.294***
				(0.026)
intercept	-0.189**	-0.004	0.118	0.125
	(0.076)	(0.143)	(0.147)	(0.084)
Observations	31	31	31	31

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 7 – Table of results; model 1 using RLM; dataL

	Dependent variable:		
	CV9-15	CV16-22	CV23-29
LCC	0.027**	-0.023	0.029
	(0.011)	(0.039)	(0.033)
HHI	-0.00001	-0.0002*	0.00002
	(0.00004)	(0.0001)	(0.0001)
GDP in origin	0.0002*	0.001**	0.001***
	(0.0001)	(0.0003)	(0.0003)
GDP in destination	0.0001	0.0003	-0.00002
	(0.0001)	(0.0003)	(0.0003)
evening flight	0.016	0.056	0.072*
	(0.016)	(0.048)	(0.044)
morning flight	0.033**	0.084**	0.029
	(0.013)	(0.039)	(0.037)
price increase 2	0.227***		
	(0.012)		
price increase 3		0.122***	
		(0.035)	
price increase 4			0.342***
			(0.092)
intercept	0.003	0.457	-0.143
	(0.102)	(0.301)	(0.288)
Observations	38	38	38
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.038***	0.028**	0.040***	0.043***
	(0.014)	(0.012)	(0.013)	(0.010)
HHI	0.00002	-0.00001	-0.0001	-0.0001
	(0.0001)	(0.00004)	(0.00004)	(0.00003)
GDP in origin	0.0003**	0.0003**	0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP in dest.	0.00004	-0.00001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
evening flight	0.013	-0.005	-0.0003	0.007
	(0.020)	(0.016)	(0.016)	(0.013)
morning flight	0.006	-0.021	-0.014	-0.0001
	(0.017)	(0.015)	(0.014)	(0.011)
price increase 5	0.246***			
	(0.072)			
price increase 6		0.255***		
		(0.018)		
price increase 7			0.419***	
			(0.031)	
price increase 8				0.295***
				(0.028)
intercept	-0.068	0.023	0.130	0.116
	(0.131)	(0.107)	(0.110)	(0.087)
Observations	38	38	38	38
Note:	*p<0.1; **p<0.05; ***p<0.01			

Appendix 8 – Table of results; airline market share; dataC

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	0.004	0.009	-0.018	0.028
	(0.017)	(0.022)	(0.045)	(0.046)
HHI	0.0001**	0.00001	-0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP in origin	0.001***	0.0001	0.001***	0.002***
	(0.0002)	(0.0002)	(0.0004)	(0.0005)
GDP in dest.	0.001***	-0.00000	0.0001	-0.0002
	(0.0001)	(0.0002)	(0.0003)	(0.0004)
evening flight	-0.088**	-0.003	0.044	0.069**
	(0.036)	(0.028)	(0.033)	(0.032)
morning flight	-0.071***	0.033*	0.107***	0.064
	(0.023)	(0.017)	(0.037)	(0.041)
price increase 1	0.252***			
	(0.025)			
price increase 2		0.225***		
		(0.014)		
price increase 3			0.068	
			(0.061)	
price increase 4				0.270**
				(0.137)
airl. market sh.	-0.360*	0.146	0.207	0.189
	(0.208)	(0.204)	(0.409)	(0.381)
intercept	-0.197	-0.038	0.213	-0.448
	(0.157)	(0.157)	(0.377)	(0.341)
Observations	31	31	31	31
R2	0.879	0.904	0.533	0.531
Adjusted R2	0.835	0.869	0.363	0.361

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.082***	0.042**	0.047**	0.048***
	(0.022)	(0.018)	(0.022)	(0.013)
HHI	0.0001	-0.00002	-0.0001	-0.00004
	(0.0001)	(0.00004)	(0.0001)	(0.00003)
GDP in origin	0.0002	0.0004***	0.001**	0.0003**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
GDP in dest,	0.0003*	0.0001	0.0001	0.00000
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
evening flight	0.062**	0.030	0.061	-0.010
	(0.028)	(0.024)	(0.057)	(0.013)
morning flight	0.031*	-0.023*	-0.014	0.002
	(0.017)	(0.012)	(0.016)	(0.010)
price increase 5	0.176**			
	(0.083)			
price increase 6		0.236***		
		(0.024)		
price increase 7			0.515***	
			(0.121)	
price increase 8				0.275***
				(0.025)
airl. market sh.	-0.006	-0.033	-0.123	0.073
	(0.201)	(0.116)	(0.270)	(0.094)
intercept	-0.170	0.035	0.263	0.057
	(0.162)	(0.091)	(0.223)	(0.081)
Observations	31	31	31	31
R2	0.384	0.883	0.612	0.882
Adjusted R2	0.160	0.840	0.471	0.840

Appendix 9 – Table of results; quality of the service; dataC

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	0.012	-0.002	-0.061	-0.008
	(0.020)	(0.022)	(0.044)	(0.048)
HHI	0.0001*	0.00001	-0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GDP in origin	0.001***	0.0001	0.001***	0.002***
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
GDP in dest.	0.0005***	-0.00001	-0.00000	-0.0002
	(0.0001)	(0.0002)	(0.0003)	(0.0004)
evening flight	-0.095**	0.0002	0.056*	0.080***
	(0.039)	(0.030)	(0.033)	(0.031)
morning flight	-0.067**	0.032	0.114***	0.073*
	(0.026)	(0.020)	(0.035)	(0.040)
price increase 1	0.269***			
	(0.028)			
price increase 2		0.221***		
		(0.015)		
price increase 3			0.066	
			(0.062)	
price increase 4				0.232*
				(0.132)
quality of serv.	-0.002	-0.059	-0.329**	-0.318
	(0.063)	(0.080)	(0.159)	(0.210)
intercept	-0.304*	0.044	0.419	-0.276
	(0.168)	(0.150)	(0.298)	(0.266)
Observations	31	31	31	31
R2	0.867	0.904	0.567	0.560
Adjusted R2	0.819	0.868	0.410	0.400

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.082***	0.042**	0.047**	0.048***
	(0.022)	(0.018)	(0.022)	(0.013)
HHI	0.0001	-0.00002	-0.0001	-0.00004
	(0.0001)	(0.00004)	(0.0001)	(0.00003)
GDP in origin	0.0002	0.0004***	0.001**	0.0003**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
GDP in dest,	0.0003*	0.0001	0.0001	0.00000
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
evening flight	0.062**	0.030	0.061	-0.010
	(0.028)	(0.024)	(0.057)	(0.013)
morning flight	0.031*	-0.023*	-0.014	0.002
	(0.017)	(0.012)	(0.016)	(0.010)
price increase 5	0.176**			
	(0.083)			
price increase 6		0.236***		
		(0.024)		
price increase 7			0.515***	
			(0.121)	
price increase 8				0.275***
				(0.025)
quality of serv.	-0.006	-0.033	-0.123	0.073
	(0.201)	(0.116)	(0.270)	(0.094)
intercept	-0.170	0.035	0.263	0.057
	(0.162)	(0.091)	(0.223)	(0.081)
Observations	31	31	31	31
R2	0.384	0.883	0.612	0.882
Adjusted R2	0.160	0.840	0.471	0.840

Appendix 10 – Table of results; interaction of LCC and LT route; dataC

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	0.044**	0.019	-0.089	-0.010
	(0.022)	(0.019)	(0.061)	(0.063)
HHI	-0.00004	-0.0001	0.0001	0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
GDP in origin	0.0004**	-0.00002	0.002***	0.002***
	(0.0002)	(0.0003)	(0.0004)	(0.001)
GDP in dest.	0.0003***	-0.0001	0.0003	-0.00004
	(0.0001)	(0.0002)	(0.0003)	(0.0004)
evening flight	-0.106***	-0.009	0.058*	0.077**
	(0.029)	(0.032)	(0.031)	(0.031)
morning flight	-0.081***	0.023	0.126***	0.071*
	(0.021)	(0.023)	(0.035)	(0.041)
price increase 1	0.271***			
	(0.022)			
price increase 2		0.224***		
		(0.016)		
price increase 3			0.095*	
			(0.057)	
price increase 4				0.281**
				(0.134)
LCC*leisure	-0.109***	-0.051	0.175**	0.100
	(0.034)	(0.061)	(0.079)	(0.086)
intercept	0.150	0.240	-0.420	-0.767*
	(0.207)	(0.368)	(0.358)	(0.405)
Observations	31	31	31	31
R2	0.900	0.908	0.589	0.547
Adjusted R2	0.864	0.875	0.439	0.382

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.095***	0.056***	0.061**	0.047***
	(0.032)	(0.021)	(0.024)	(0.016)
HHI	-0.00001	-0.0001	-0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.00004)
GDP in origin	0.0001	0.0003	0.0004	0.0003**
	(0.0002)	(0.0002)	(0.0003)	(0.0001)
GDP in dest,	0.0002	-0.00000	0.00003	-0.00001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
evening flight	0.058*	0.026	0.060	-0.012
	(0.030)	(0.025)	(0.062)	(0.014)
morning flight	0.028*	-0.027**	-0.015	-0.002
	(0.017)	(0.012)	(0.019)	(0.010)
price increase 5	0.208**			
	(0.100)			
price increase 6		0.235***		
		(0.021)		
price increase 7			0.509***	
			(0.095)	
price increase 8				0.276***
				(0.023)
LCC*leisure	-0.042	-0.043	-0.031	-0.008
	(0.047)	(0.030)	(0.052)	(0.022)
intercept	-0.003	0.200	0.331	0.123
	(0.172)	(0.157)	(0.266)	(0.112)
Observations	31	31	31	31
R2	0.397	0.889	0.614	0.881
Adjusted R2	0.178	0.849	0.473	0.838

Appendix 11 – Table of results; interaction of FSC and BT route; dataC

	Dependent variable:			
	CV2-8	CV9-15	CV16-22	CV23-29
LCC	-0.066***	-0.033	0.064	0.061
	(0.019)	(0.058)	(0.058)	(0.057)
HHI	0.0002***	0.0001	-0.0003*	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
GDP in origin	0.001***	0.0002	0.001**	0.001***
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
GDP in dest.	0.001***	0.0001	-0.0002	-0.0003
	(0.0001)	(0.0001)	(0.0004)	(0.0005)
evening flight	-0.106***	-0.008	0.051	0.071**
	(0.027)	(0.030)	(0.031)	(0.031)
morning flight	-0.076***	0.026	0.111***	0.062
	(0.019)	(0.021)	(0.034)	(0.039)
price increase 1	0.275***			
	(0.022)			
price increase 2		0.224***		
		(0.016)		
price increase 3			0.084	
			(0.054)	
price increase 4				0.276**
				(0.133)
FSC*business	-0.110***	-0.053	0.138*	0.058
	(0.032)	(0.060)	(0.074)	(0.078)
intercept	-0.495***	-0.073	0.568	-0.248
	(0.155)	(0.164)	(0.378)	(0.344)
Observations	31	31	31	31
R2	0.905	0.909	0.571	0.536
Adjusted R2	0.870	0.876	0.416	0.367

	Dependent variable:			
	CV30-36	CV37-43	CV44-50	CV51-57
LCC	0.060*	0.017	0.024	0.042***
	(0.032)	(0.025)	(0.043)	(0.014)
HHI	0.0001	0.00002	-0.0001	-0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.00004)
GDP in origin	0.0002	0.0004***	0.001**	0.0003*
	(0.0002)	(0.0001)	(0.0002)	(0.0002)
GDP in dest.	0.0004*	0.0001	0.0002	0.00001
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
evening flight	0.060**	0.028	0.060	-0.011
	(0.030)	(0.025)	(0.061)	(0.014)
morning flight	0.031*	-0.024**	-0.013	-0.001
	(0.017)	(0.010)	(0.016)	(0.010)
price increase 5	0.203**			
	(0.099)			
price increase 6		0.235***		
		(0.022)		
price increase 7			0.518***	
			(0.099)	
price increase 8				0.276***
				(0.024)
FSC*business	-0.032	-0.038	-0.041	-0.005
	(0.045)	(0.028)	(0.049)	(0.021)
intercept	-0.237	-0.052	0.131	0.082
	(0.283)	(0.129)	(0.169)	(0.109)
Observations	31	31	31	31
R2	0.393	0.889	0.616	0.881
Adjusted R2	0.172	0.848	0.476	0.838