Erasmus University Rotterdam | Erasmus School of Economics | Master's Thesis

The impact of entry by high capacity airlines on incumbents

Abstract

This master's thesis examines empirically the impact of market entries by high capacity airplanes on the incumbent airlines' strategy in terms of airfare, aircraft capacity and frequency of flights. Using a dataset of the U.S. aviation sector from 1993 - 2013, I find that entries by high capacity airplanes have a significant negative impact on the incumbents' airfare level. Once a new airline enters the market with a high capacity airplane, incumbents tend to decrease their overall capacity, primarily by downsizing frequency but also aircraft capacity. These findings are based on a dynamic panel data model. Sensitivity analyses support the results and hint at a positive correlation between aircraft size of the entering airline and effect intensity. This research is valuable for market entering airlines just as incumbents facing competitive challenges through high capacity airlines.

Keywords: capacity, aviation sector, market entries

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Introduction

This empirical analysis focuses on capacity issues in the aviation sector. Concerning Wittenberg et al. (2001), air traffic has been growing tremendously since the 1990's and is expected to grow at even higher rates in the following decades. Not only airports face enormous capacity problems which aggravate airport and airspace congestion, also airlines see themselves in a situation where they are forced to optimize their airplane capacity due to an increasing number of passengers or increasing demand for efficient high-capacity airplanes. At the same time, airplane manufacturers like Airbus or Boeing offer an ever-growing airplane capacity. This opens the question, to what extent airlines tackle their capacity problem and, if they do, how incumbent airlines react to the competitors' strategy. In particular, this master's thesis investigates the impact of high capacity market entries on the incumbents' strategy.

Recent literature points out three key determinants which airlines use to create market power: (1) airplane capacity, (2) frequency of flights and (3) airfare. Incumbent airlines are therefore expected to adjust these determinants to stabilize their market power when an airline enters the market. However, economic theory and evidence from previous research does not indicate a clear direction: In response to high capacity market entries, airlines might either decrease their *capacity* due to a possible oversupply of seats, or increase capacity to adapt their strategy to the growing market. The direction of an airline's *frequency* adjustments remains unclear, as well. Depending on capacity choices, airlines might either increase their frequency with lower capacity airplanes or decrease frequency using high capacity ones. Whereas some evidence indicates that a high frequency of flights results in a crucial market advantage, the increasing need for efficiency through high capacity airplanes should as well be taken into consideration. In terms of *airfare*, airlines might on the one hand follow economic theory and enter a price competition when an additional airline enters the market. On the other hand, previous literature finds that reductions in airfare might lead to profit cannibalization with an overall negative outcome for the airline. The impact on these three determinants will here be investigated in three separate hypotheses.

This study is based on an empirical analysis using a dynamic panel data model, the Arellano-Bond estimation. The dataset consists of quarterly observations in the U.S. aviation sector in the period from 1993 to 2013.

In the following chapter, I am going to provide a literature review on how capacity problems in general have been investigated in previous literature, followed by a deeper analysis of the literature on aircraft capacity and its consequences. Three hypotheses are constructed in this section. The third and fourth part contains methodology and dataset description. The fifth and following parts present results, a conclusion and comments on limitations & future research.

Literature Review & Hypotheses

One of the first to examine capacity was Manne (1961). In his paper he analyzes the optimal degree of excess capacity for facilities such as steel plants or superhighways with respect to economies of scale and opportunity costs for unsatisfied demand. He develops a model to adjust capacity to the actual demand of steel plants or superhighways to optimize utility. The model's main target is to avoid suboptimal capacity planning which leads to excess capacity or supply shortages. Manne develops a model considering businesses with only one product. Ho & Fang (2013) add to Manne's model by taking into account several products within a single company. They state that manufacturers have to allocate their capacity to individual product lines to meet the market's demand and maximize profits. In their model, they assume that the demand for products is uncertain. The model's goal is therefore to avoid both excess and shortage of products.

As it is the case in practice, Ho & Fang take finite capacity, substitution effects, as well as holding and shortage costs into consideration. Due to finite capacity, manufacturers cannot simply increase a product line's capacity until it hits the demand. While increasing the capacity on one product line, the capacities of other product lines need to be decreased simultaneously. Additionally, they mention that substitution effects among product lines might lead to lower demand for one product while increasing the supply for the substitute good. This in turn makes capacity adjustments for both products necessary.

Ho & Fang develop a model that can be used as a tool to assist managers allocating finite capacity to product lines. However, by adjusting capacity between product lines, several assumptions concerning the flexibility of capacity are made. The most important one is that investments are reversible. He & Pindyck (1992) analyze the capacity choice problem for irreversible investments. They find that the irreversibility of investments in combination with uncertainty in demand has a significant impact on the capacity choice of companies. In case investments are irreversible and demand is uncertain, the capital invested in the firm's capacity tends to be lower as compared to reversible investments. At the same time, the firm value increases since uncertain demand and the possibility to invest in additional capacity create valuable options. It is important to note that He &

Pindyck assume stepless investments in their model, ignoring the existence of fixed costs or lump sum investments. This opens the question whether fixed costs should be taken into account while determining the optimal capacity level of investments.

According to Pan (2007) the cost structure in the hotel business consists of large fixed parts and low variable ones. For investments in hotel facilities and the determination of hotel capacity, the existence of fixed costs plays a significant role. Pan finds that the amount of fixed costs of investments increases with the capacity of investments. While this seems to be obvious for the hotel sector or other businesses with high initial investment costs, this might not hold for sectors, characterized by comparably low initial investment costs. Pan's model shows that an increase in hotel capacity has a negative impact on hotel room rates, especially in the low season. This can be explained by the simple economic principle that an oversupply of goods decreases price levels and - vice versa - a scarcity of goods and services increases price levels.

Since the volume of goods and services on the market appears to be mainly determined by the capacity which firms have to produce goods and offer services, the question arises whether a firm's capacity influences the prices through possible over- and undersupply. Lízal & Tashpulatov (2014) investigate to what extent capacity cutting strategies for the electricity market in England and Wales are utilized to decrease the supply and increase the overall price level. They find empirical evidence that in some parts of the market this type of tacit collusion takes place. Their findings go in line with Sweeting (2007), observing a divestiture of capacity to increase the overall price level in the United Kingdom. His study refers to the case of *National Power* and *PowerGen* (today *E.On*), two electricity providers in the UK.

Because companies are able to influence prices and market volume through the level of investment in capacity, it seems obvious that capacity adjustments can be utilized as a strategic means to maintain market power. In other words, capacity could be used ex ante to deter new firms from entering the market. Spence (1977) mentions two strategies to make a new entrant unprofitable: (1) as mentioned above, incumbent companies could increase capacity to that level, at which prices are too low for young firms to enter. Due to high investment costs and a low marginal yield, it might not be profitable for small companies to enter the market. (2) By creating excess capacity which makes additional market supply needless, incumbent firms could create an entry barrier for new companies. These strategies have also been subject for investigation by Spulber (1981) and Lieberman (1987). Spulber states that two crucial conceptions to deter entries have been made. Following the *Sylos Postulate,* firms constantly offer a high output on the market to deter entry. The *Excess Capacity Hypothesis,* however, states that a high level of unused capacity built up by incumbent firms, deters the entry of new competitors. Lieberman finds that the theoretical conception of excess capacity to deter entry does indeed work, though a lack of evidence suggests that this ex ante strategy is not very common in practice. He mentions that unused capacity is rather built up to compensate demand volatility or has been the result of investment lumpiness.

So far, this thesis provides a brief literature review of how capacity is examined as a tool for strategic ex ante decisions. The majority of researchers develops a model which aims to maximize the incumbents' utility and maintain the market power by determining the optimal level of capacity. High capacity - used or unused - seems to be a major competitive advantage which companies use to gain or protect their current market share. However, a strategic realignment can also be the *result* of changes in a market's capacity. In the following, I am going to investigate the determinants of an airline's strategy and how these are influenced by changes in capacity.

Recent studies in the aviation sector detect three main determinants airlines use to gain and hold their market share: Wei & Hansen (2007) mention that two main determinants are the *aircraft size* and the *frequency* of flights on a given route. Brons et al. (2002) among others state that the *airfare* is a crucial determinant for the demand of flights. The latter begs the question whether airlines change their prices in response to an increased supply of goods and services in the market. Following basic economic principles, a good's price increases when the supply of that good decreases. This principle might also hold for an increasing capacity in the aviation sector. Malighetti et al. (2009) analyze the relation of seat supply to ticket prices by studying a Ryanair case. They find that airfares tend to decrease as the number of seats which an airline offers increases. Vice versa, ticket prices tend to increase over time since tickets are being sold and the available capacity in form of free seats decreases. Malighetti et al. derive a price function which features two main premises: An airline's capacity is restricted and tickets are "perishable". Because airlines cannot produce infinite seats, an airplane might be booked out at some point. The scarcity of seats in combination with the travelers' demand for flights influences the ticket price. Malighetti et al. state that airlines make use of dynamic pricing to sell flight tickets for the maximum price under the premise to sell all tickets available. Using this concept, airlines do not determine a booking policy when the flight is scheduled but observe the state of ticket bookings over time to decide on the price of a ticket when the request arrives (see Pak & Piersma, 2002). Like Malighetti et al. mention, ticket prices tend to increase until the very last minute before the flight. According to them, the price trend closely resembles a hyperbola. Furthermore, they state that airplane seats are perishable, meaning that the ticket's value is zero after the airplane takes off. The airline's goal is therefore to sell all tickets before the tickets expire. In particular for low cost carriers this is a crucial goal because their success is based on a sensitive combination of load factors, ticket prices and operating costs. Additionally, they mention that after scheduling the flight, marginal costs in relation to the number of passengers are practically zero. Thus, ticket prices represent an important revenue contribution. This goes in line with Alderighi et al. (2012). They investigate yield management concepts of airlines and find that demand fluctuations, uncertainty about the travelers' departure date and consumer heterogeneity in combination with the restriction of limited capacity and the perishable nature of seats make yield management a complex decision. In general, they distinguish between two main yield management concepts. The first one is the traditional yield management concept used by full service carriers. The second concept is a down-graded version, the simplified yield management, which is being used by low cost carriers. Whereas the traditional management includes numerous regulating screws to segment the market by product differentiation, distribution or extra services next to the time of booking and the choice of flight, the simplified management just features the time of booking and the choice of flight. Low cost carrier flights are therefore not-differentiated products which do not come with extras like e.g. drinks & food during the flight or frequent traveler programs.

By investigating the effect of additional competition in the market on price determination, they find that in the full-service-carrier segment, business fares are more sensitive to additional competition as compared to fares of leisure flights. Airfares for leisure flights react less sensitive to increased competition in the market. Additional competition by a low cost carrier, however, has nearly the same effect on leisure and business airfares. This is strongly contrastive to the finding of Malighetti et al. (2009) who find that the low cost carrier market is a separate market which does not compete with the full-service-market.

Recent literature on revenue management has shown that airlines tend to increase prices as the supply of seats decreases. Vice versa, prices tend to increase as additional seats are offered on the market. Thus, a possible inference might be that prices decrease as new airlines enter the market and offer additional flights. Joskow et al. (1994) investigate empirically the impact of market entries on incumbents' prices in the market. Using a dataset with 40 airlines in the US airline market for the years 1985 - 1987, they find that a market entry lets incumbents decrease airfares, whereas a market exit in turn increases the price level on the market. Since the airline deregulation act in 1978 in the USA, the market is open for a price competition which airlines increasingly face to gain costumers. Additionally, following Garrow et al. (2006), the availability of online search engines for flights even increased the consumer's price awareness. Nowadays, the comparison of ticket prices and booking of the cheapest flights, have become much easier through the availability of certain information on the internet. Flight search engines, therefore, increase the customers' awareness of prices and create greater competition among airlines on one market.

Considering the facts mentioned above, it seems obvious that airlines decrease prices in reaction to capacity increases through market entries. The entry via a high capacity airplane might even amplify the incumbents' reaction because the entering airline is expected to attract more passengers than usual airlines and to realize crucial cost advantages through economies of scale. Based on this, I am going to define the following hypothesis:

Hypothesis 1: The market entry of an airline via a high capacity plane lowers the incumbents' airfares on the market.

Following the hypothesis above, entering high capacity airlines could lead incumbents to decrease airfares on their route. Carpenter & Hanssens (1994) examine the impact of airfares on additional profit and market size by considering the example of the French airline *Union des Transports Aeriens* (UTA). They find that great decreases in airfares can increase the market size, whereas low decreases do not increase the market size but rather cannibalize profits. Great discounts might increase the market size because, first, lower airfares attract new customers and second, passengers travel more often. Low discounts do not necessarily attract new customers but let existing customers travel at cheaper rates which results in lower profits. These findings go in line with the previously mentioned study of Joskow et al. who find evidence that, in case of a market entry, incumbents decrease their prices significantly. Additionally they find that airlines increase the number of flights which, in effect, increases the number of passengers transported. In case of a market exit, the effect turns the other way around, correspondingly. A market exit considerably increases fares and decreases output.

Therefore, the investigation how incumbents strategically react to the introduction of larger airplanes to the market in terms of airplane size stands to reason. Considering Carpenter & Hanssens' findings, several options seem to be plausible: Because of an increase in demand, airlines could simply offer more flights. Alternatively, due to cost efficiency, an airline could have an incentive to use larger airplanes without changing the frequency. This way the incumbent airline could keep up with the competitors in the market and realize a costs advantage through economies of scale. On the other side, because incumbent airlines might fear a market oversupply, they could react by decreasing seat capacity of their aircrafts on that route, or alternatively decrease frequency. Furthermore, to build up excess capacity might not be an optimal strategy in the aviation sector since this business is too cost-sensitive.

Because this theory is yet to be investigated in the latest research, I will examine the impact of a market entry via high capacity airplanes on the incumbents' capacity. More specifically, I will investigate whether incumbents follow the strategy of using airplanes with a higher capacity to realize a competitive advantage or if they react with a decreasing capacity due to the fear of oversupplying the market. Following Carpenter & Hanssens' statement that airlines might adapt their strategy to increasing demand of seats, I am going to hypothesize the following:

Hypothesis 2: The market entry of an airline with a high capacity airplane will increase the competitors' average aircraft size in the market.

Like mentioned above, to an increasing demand of flights on a route, an airline could also increase the number of flights while keeping the aircraft size constant. Button & Drexler (2005) and Wei & Hansen (2007) investigate the *S-curve effect* of service frequency and capacity for the airline sector.

According to this, an airline can increase its market share at a certain point of frequency overproportionally by increasing the number of flights. Button & Drexler (2005) refute the existence of an S-curved function for service frequency on market share; instead they find a linear relation between the service frequency and market share which means that additional flights do not increase market share overproportionally. Moreover, they observe that in recent years, airlines tend to increase their airplane capacity rather than the frequency of flights. However, Wei & Hansen (2007) support the existence of an S-curved effect. They build a nested logit model including seat availability, fare, an airline's market share and the total air travel demand for a duopoly market. In their study they find that airlines can gain higher turnovers by an increase in service frequency at a certain level as compared to an increase in aircraft's size. Furthermore, while entering airlines try to realize costs advantages through economies of scale, it might be the case that incumbent airlines strive to maintain market power by creating a Unique Selling Proposition through an increased number of flights.[1] Additionally, compared to investments in larger aircrafts, an increase in frequency turns out to be the more reversible investment decision which includes the option to downsize capacity easier.

To examine the effect of the introduction of larger airplanes on the incumbents' frequency of flights, I will investigate the following hypothesis:

Hypothesis 3: The market entry of an airline with a larger capacity airplane will increase the competitors' frequency of flights on the market.

In addition to afore mentioned explanations of why airlines might change their airplane capacity and airfare, there might be more exogenous impacts. For instance, Bazargan & Hartman (2012) derive a model to optimize aircraft fleet management and replacement. They find that around 70% of an airlines' cost components belong to the fleet's operation.[2] In its annual report of FY2013, American Airlines states that 35.6% of the *total mainline operating expenses* were expenses for "aircraft fuel and related taxes". This suggests that the fuel price might impact the aircraft size externally. Morell & Swan (2006) examine to what extent airlines are affected by jet fuel prices.

[1] For further information see Reeves & Rosser (1961)

[2] Although Bazargan & Hartman derive a complex model, their paper does unfortunately not exemplify the single cost components of operational costs.

They state that at a price of $25 per barrel, the fuel price makes out 15% of an airline's total costs. Figure 1 impressively shows a tremendous increase in jet fuel price starting in year 2004 with a peak during the financial crisis in 2008. Therefore, it seems obvious that the increasing jet fuel price as a major cost driver urges airlines to organize their operations in a more efficient way. Givoni & Rietveld (2010) state that a high capacity aircraft's performance with respect to energy usage is more efficient as compared to low capacity airplanes. Because fuel prices tend to increase over time, airlines would have an incentive to invest in larger airplanes. Since an increase in jet fuel seems to affect all market participants, I am going to control for it while running the empirical analysis. At this, the jet fuel price is the same for all states in the USA. Though, the increase in fuel prices could also be caused by an increase in inflation. The *Consumer Price Index for All Urban Consumer* (CPI-U), compiled by the United States Bureau of Labor Statistics (BLS) is, among others, based on the oil price and ticket prices for flights.[3] To account for inflation, I am going to include quarterly data of the CPI-U from 1993 to 2013.

A second cost determining factor could be landing fees which are paid to cover an airport's direct costs like e.g. tracking the flights, offering a parking slot and handling passengers and luggage. Allen (1994) and Wei (2006) find that landing fee policies affect airlines and the aircraft type they use. They mention that with an increase in fees, larger aircrafts will more likely be scheduled as compared to smaller aircrafts. At first, it seems obvious that an increase in fees per landing influences an airline's choice of aircraft. However, up to date many airports charge airlines by airplane weight.[4] For instance, at the Los Angeles International Airport (LAX), passenger aircrafts with a maximum gross landing weight (MGLW) of more than 25,000 lbs. have to pay $3.78 per 1,000 lbs. of the MGLW.[5] Other airports charge airlines by the actual landed weight or the starting weight.[6] Like Allen (1994) finds out, a pricing policy based on an aircraft's weight does not encourage airlines to increase aircraft size. To create the incentive for airlines to actually use larger

[3] http://www.bls.gov/cpi/cpid1410.pdf

[4] Airports which charge landing fees based on the Maximum Growth Landing Weight are for instance Hartsfield-Jackson Atlanta International, Boston Logan International, Chicago Midway International, Miami International, Washington Dulles International or Los Angeles International.

[5] See also: *Los Angeles World Airports (2013), Rules and Regulations July 2013, Section Airport operating permits and fees*

[6] See also Morrison (1982) for an argumentation whether the landing or starting weight should be taken into account.

aircrafts, one would need a fixed price per landing which would, in turn, decrease the landing fees per passenger when the number of passengers on a flight increases. From this point of view one can consider that landing fees do not have a direct impact on the aircraft's size.

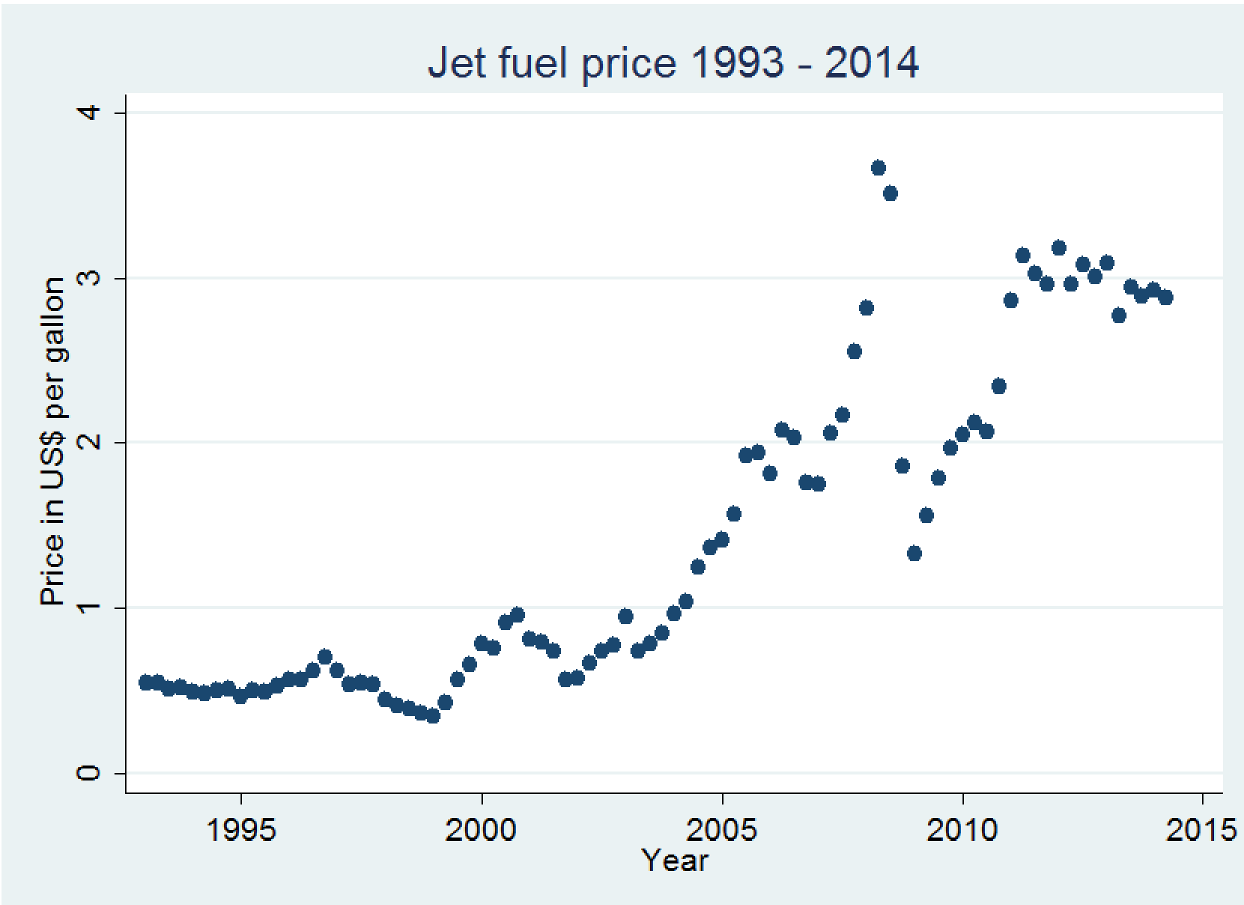

Figure 1 - Jet fuel price 1993 - 2014 on a quarterly basis - source: http://www.eia.gov/dnav/pet/hist/

The distance, however, could have a significant impact on the airplanes size: Givoni & Rietveld (2009) find that aircraft size increases with the distance to the destination airport. On the one side, the flight range could be a significant competitive advantage for airlines. On the other side, defining *markets* as airport pairs assumes that the distance between two airports is the same for all market participants. A greater feasible range of an aircraft would therefore not be a competitive advantage for that market.

A further determinant which influences strategic focus is the question whether there is a low cost carrier entering the market or already present in the market. Goolsbee & Syverson (2008) investigate the impact of a possible entry threat of a *low cost carrier* (LCC) on the competitors' fares. They do so by looking at *Southwest Airlines* which might possibly enter certain markets. Goolsbee & Syverson find that solely the threat of Southwest Airlines entering the market, makes market participants preemptively lower their fares. Furthermore, they state that airlines increase their load factor (meaning the proportion of seats filled with passengers to the seats available) with an upcoming entry threat. This indicates that the entry-threat or the existence of a low cost carrier drives airlines to work more efficiently. Goolsbee & Syverson cannot find evidence for an impact on airplane capacity or the number of flights scheduled. However, they state that they cannot rule out a change in capacity due to missing significance on this estimation. Though, Givoni & Rietveld (2009) find that in markets where low cost airlines are present, the average aircrafts' size is 14% larger as compared to markets without low cost carriers. This can be explained by two reasons: First, low cost carriers use economy-only airplanes, enabling them to place more seats per aircraft. Second, the focus of low cost carriers is on a price competition rather than a competition based on frequency. Therefore those airlines prefer larger aircrafts with a greater efficiency over a high frequency supply.

Methodology

Purpose of this study is to investigate the entry-effect of high capacity airplanes on the strategy of incumbent firms in the market. Previous literature indicates that airlines use three main determinants to adjust their strategy and maintain their market share: The airfare on a route, the frequency of flights and the capacity of aircrafts. To each determinant I define a hypothesis to investigate the impact of a market entry with a high capacity airplane on that corresponding determinant.

In hypothesis 1, I will examine the impact of high capacity entries on *airfare*. The expected contribution of the main independent variable is negative. Hypothesis 2 examines to what extent the incumbents' *aircraft capacity* is influenced by high capacity firms entering the market. Because airlines can realize cost advantages through economies of scale, the expected sign is positive. This means that in reaction to a high capacity market entry, incumbents would react by increasing their aircraft capacity. Hypothesis 3 examines the impact of an entrant's airplane capacity on the incumbent's frequency of flights. Recent research finds that frequency is a main factor to maintain market power in a market. Therefore, the expected sign in this analysis is positive, meaning that airlines react with an increased frequency to high capacity entries.

For this analysis, the advantage of panel data stands to reason because the strategic positioning of airlines is a long term decision that can only be observed by including a time-series. This prerequisite and the need to include more than a single market in this study to increase the meaningfulness, make panel data inevitable. Verbeek (2013) states that repeated observations of the same units over time enable researchers to generate more realistic models as compared to single cross-section or time-series models. Additionally, he mentions that economists can investigate changes on an individual level by using panel data. This enables the usage of different individual markets over time in this study.

Because strategy adjustments and investments in new airplanes in particular are expected to be long term decisions which require a profound analysis in advance, immediate adjustments to a competitor's high capacity entry are unlikely to be observed. Therefore, all independent and control variables in the panel data models are lagged by one quarter. Furthermore, because entry effects do not only affect the competitors' strategy in the moment of entry but rather influence their strategy in the long term, one would expect dynamic effects taking place. Beck & Katz (2011) discuss several options to model dynamic time-series cross section data. To include the dependent variable as a lagged instrumental variable is one option which is featured by the *Arellano-Bond-estimation*. This estimator uses the *Generalized Method of Moments (GMM)*[7] to include the dependent variable efficiently as a lagged instrumental variable. A common alternative method is the two-stage least squares method (2SLS). Though, in comparison to the GMM, the 2SLS entails a trade-off between the lag distance and the number of time periods used in the dataset. The consequence of an additional lag period is the loss of one usable period in the dataset (Roodman, 2009b). By using the GMM, missing observations are filled with zeros. Roodman (2009a) states that the Arellano-Bond estimator is particularly designed for "small T, large N" datasets, meaning panel data which consists of observations over a few periods in numerous panels, since no periods are lost by applying the GMM. Furthermore, he mentions that the Arellano-Bond estimator estimates a linear functional relationship taking into account independent variables which are not strictly exogenous and feature fixed individual effects. Using the Arellano-Bond estimator, panel-specific heterogeneity will usually be removed by the first differentiation of the regression equation, so-called *difference GMM*. For unbalanced panel data this entails the problem that gaps in panels will be magnified through the differentiation. Based on the work of Arellano & Bond (1991), Blundell & Bond (1998) enhance the difference GMM by developing a *system GMM* which assumes that the first differences of the instrument variables are uncorrelated with fixed effects. Bun & Windmeijer (2010) mention that the system GMM estimates moment conditions for first differences and moment conditions for levels simultaneously. According to Roodman (2009a), this allows the model to use more instruments to increase its efficiency. Therefore, in this study I am going to regress an Arellano-Bond model with system GMM. The maximum number of lags being used as instruments for the dependent variable is set to four periods. The general Arellano-Bond equation is the following:

[7] See also Hansen, L. P. (1982) - *Large Sample Properties of Generalized Method of Moments Estimators*, Econometrica, Vol. 50, No. 4, pages 1029-1054

$$y_{it} = \alpha_0 + ß * y_{i,t-1} + \delta_{it} * x_{it} + [\ldots] + u_i$$

where y_{it} is the dependent variable and $y_{i,t-1}$ the lagged dependent variable included as an independent variable. The first differentiation is constructed as follows:

$$\Delta y_{it} = ß * \Delta y_{i\ t-1} + \delta_{it} * \Delta x_{it} + [\ldots] + \Delta u_i$$

The model is tested for autocorrelation in first differenced errors and the goodness of fit. The latter is tested by using the Wald Chi-Square statistic. The existence of autocorrelation in first differenced errors is tested by the Arellano-Bond test for autocorrelation. By means of the *Sargan Test* one can test whether the model might be over-identified. However, Chao et al. (2014) state that the Sargan test is not robust to a large number of instruments. Additionally, Roodman (2009b) finds that an instrument count above the ideal does not make the GMM inconsistent. Chao et al. propose an alternative testing procedure which is robust to numerous instruments and heteroskedasticity. Though, this recent test did not find recognition in latest research and is not featured by STATA packages, yet.

In this analysis, I am going to take *markets* as the individual level. Following Brueckner (2013), I define an airport pair as a market. All observations on individual level in the dataset are observed on a market-time-level which is the prerequisite for the use of panel data. The initial dataset has been collected on a time-market-airline-level. Therefore, I prepare the dataset for the use of panel data. For instance, the variable for passenger airfare on a certain route, has been observed for individual markets over time and for all airlines in the market. By preparing the dataset for panel data, it will be collapsed to a market-time-level by taking the mean of the airfares offered by the individual airlines. In contrast to that, market size will be derived by the sum of the number of passengers transported by the corresponding airlines. Furthermore, individual-independent data like, for instance, the consumer price index, GDP or jet fuel price, were initially observed for all markets per quarter. In these cases there was no necessity to collapse data. Because this analysis is based on a dataset from 1993 to 2013, time fixed effects are expected to play a role. All regressions will therefore take time fixed effects into account by including time dummies.

The main independent variables in the analyses are related to *high capacity aircrafts*. Due to the non-existence of literature on this, I am going to define an aircraft to be large if the aircraft's capacity is at least 1.5 times larger than the market average. Capacity in turn is measured by seats available per flight per aircraft. Subsequent to the panel data regression, I am going to conduct a sensitivity analysis by defining airplanes to be large if they are 1.25 and 1.75 times larger than the market average. These results will be compared with the base model.

To account for high capacity airplanes in the regression analysis, the dummy variable *market_entry* will turn one if there is a market entry of a high capacity airplane in that particular market for that particular quarter. This dummy will only turn one if the entering airline did not offer flights on the market in any period before. To control for ticket prices on a specific route, the variable *fare_mean* indicates the average ticket price on a specific route per quarter. In markets with only one airline, *fare_mean* represents the average ticket price within this quarter. In case two or more airlines offer flights on this route, *fare_mean* represents the average of all airfares of all airlines. The number of carriers competing in the market and the *Herfindahl-Hirschmann-index* (HHI) on a route are likewise crucial control variables included in this analysis. The HHI is a measure for market concentration and increases when a great proportion of market power is bundled among one or a few airlines (see also Rhoades, 1993). Connected to the market share of the participants, it seems reasonable to control for the number of airlines in a market. The control variable *n_carr* counts the number of market participants for the market observed. The use of this variable stands to reason because Bresnahan & Reiss (1991) find that the influence of the competitive conduct is the greatest if there are already three to five participants in the market. Starting with the sixth market participant, the strength of the influence on the competitive conduct declines. The HHI and the number of airlines competing in the market are expected to be negatively correlated. Because in concentrated markets the number of competitors tends to be lower as compared to less concentrated markets, the entry effect of an additional airline is expected to be a greater. However, in less concentrated markets one would expect this effect to be weaker. Furthermore, the control variable *lcc_on_route* indicates if there is a low cost carrier in that particular market. Since Givoni & Rietveld (2009) find that in markets where low cost airlines are present, the average aircrafts' size is 14% larger as compared to markets without low cost carriers, it seems reasonable to control for it. In case there is at least one low cost carrier present, the dummy variable turns one and zero otherwise.

Since external impacts might have a significant influence on the overall aviation market, I include the *Gross Domestic Product (GDP)* as well as *jet fuel price* in a preliminary analysis. The natural logarithm of the GDP rather than the absolute value will be taken into consideration, because the change in GDP is of particular importance. Due to the huge impact of the jet fuel price on the profits of airlines (see annual report of FY2013, American Airlines), price changes are expected to have a significant impact on the airlines' strategy. The tremendous increase in jet fuel price in recent years (see figure 1) gives another reason to control for it. Analogous to GDP, the jet fuel price will mainly be included via the natural logarithm. Though, the use of GDP and jet fuel price might entail two problems: First, GDP and jet fuel price are expected to be positively correlated. Second, the tremendous increase in GDP and jet fuel price might intrinsically be meaningful, but could also be caused by inflation. To take these two concerns into account, the GDP and jet fuel price will in a second analysis be replaced by the *consumer price index for all urban consumers* (CPI-U). Like mentioned in the literature review, the general concept of landing fees might have an impact on an airline's choice of aircraft size. Nevertheless, because the MGLW increases almost proportionally with the number of seats, airports do not create an incentive to use larger airplanes. Figure A1 shows the relation of the number of seats per aircraft on the maximum gross landing weight. Included are all major passenger aircrafts being offered by *Boeing Inc.* and *Airbus S.A.S.*

In hypothesis H1, I am going to investigate the impact of a market entry via a high capacity airplane on the incumbents' airfare. The dependent variable is the quarterly average airfare of all airlines in the market excluding the entering airline. Because less the absolute value than the change in airfare is of particular interest, I am going to estimate the natural logarithm. Since the entry's impact is expected to be delayed, I am going to lag the independent variables by one quarter. The main independent variable is the dummy variable *entry_large* which turns one if there is a high capacity entry in that market for that period and zero otherwise.

In the regression for hypothesis 1, I am going to control for several factors: The variable *herf_route* is the Herfindahl index on the individual route and controls for market concentration, whereby $\text{Herfindahl index} = \{x \in \mathbb{R} \mid 0 \leq x \leq 1\}$. To account for the total number of airlines in the market, I am going to include *n_carr* in the regression. With an increasing number of competitors, the actual impact of an airline entering the market is expected to decline. The dummy variable *lcc_on_route* indicates whether there is a low cost carrier existent in the market. The variable *CPIU* is a control variable for inflation.

The regression is run as a base model, as well as with several specifications to test the robustness. The base model uses the Arellano-Bond estimation including all control variables mentioned. As a robustness check, I am going to test several combinations of control variables (see for example table 4).

Since market concentration might have a significant impact on market response to an airline's entry, I am also going to conduct the regression, first, with a dataset only consisting of observations in markets with a high market concentration and second, with a low market concentration. The threshold is a Herfindahl index of 0.7. The same procedure is applied for the number of participants in the market. Since Bresnahan & Reiss (1991) find out that the sixth market participant will have a weaker impact on the market conduct as compared to the market participants entering before, I am going to run the analysis first, only for observations with less than six market participants and second, with six or more market participants. Additionally, since the terroristic attacks of the 11th of September in 2001 put some extraordinary conditions on the market, it might not be reasonable to include observations after the 11th of September to draw conclusions on the regular behavior of market participants in the aviation sector. To account for that, I am taking the base model and estimating the results with the dataset while excluding all observations after the second quarter of year 2001.

The estimated base model equation is as follows:

$$avfarelog_{it} = \alpha * avfarelog_{i,t-1} + ß_0 + ß_1 * entrylarge_{i,t-1} + ß_2 * herfroute_{i,t-1} + ß_3 * ncarr_{i,t-1} + ß_4 * lcconroute_{i,t-1} + ß_5 * CPI_{i,t-1} + quarter_t + u_{it}$$

where $avfarelog_{it}$ describes the natural logarithm of the incumbents' average airfare per market and quarter. This dependent variable is also included as a lagged instrumental variable to include dynamic effects. $entrylarge_{i,t-1}$ is a dummy indicating whether an airline enters the market with a high capacity aircraft in the individual markets per quarter. Similar to the control variables, this independent variable is lagged by one quarter. The variable $herfroute_{i,t-1}$ represents the Herfindahl index on a particular route for each quarter, $ncarr_{i,t-1}$ counts the number of participants in the market on a market-time level and $lcconroute_{i,t-1}$ represents a dummy indicating if a low cost carrier is present in the particular market-time combination. $CPI_{i,t-1}$ is the *Consumer Price Index for All Urban Consumers* (CPI-U). This control variable is identical for all markets and varies over time. $quarter_t$ is a time dummy which makes it possible to account for time fixed effects. u_{it} stands for the error term in this model.

In hypothesis 2, the impact of a high capacity market entry on the incumbents' airplane size in the market is examined. In this regression, the dependent variable is the average airplane capacity of all market participants per market-time combination. The entering airline's aircraft size is excluded from the market average. The capacity is measured by the seats per airplane. Because the change in capacity is rather important than the absolute capacity, I am going to take the natural logarithm of the number of seats per aircraft. Similar to hypothesis 1, the airplanes' capacity is included as a lagged instrumental variable.

The main independent variable is the dummy *entry_large* which turns one if there is a market entry via a high capacity airplane in that market time combination and zero otherwise. The set of control variables is composed like in hypothesis 1, including Herfindahl index for individual routes, number of carriers in the market, a dummy indicating if there is a low cost carrier in the market and the consumer price index CPI-U. Time fixed effects will be observed by a time dummy.

The estimated equation is as follows:

$$avcap\_log_{it} = \alpha * avcap\_log_{i,t-1} + ß_0 + ß_1 * entrylarge_{i,t-1} + ß_2 * herfroute_{i,t-1} + ß_3 * ncarr_{i,t-1} + ß_4 + ß_5 * lcconroute_{i,t-1} + ß_6 * CPI_{i,t-1} + ß_7 * quarter_t + u_{it}$$

In this equation $avcap_{it}$ describes the natural logarithm of the average number of seats per airline on a market-time level. $entrylarge_{i,t-1}$ is the dummy, indicating whether an airline enters the market with a large aircraft in the individual markets per quarter. The variable $herfroute_{i,t-1}$ represents the Herfindahl index on a particular route for each quarter and $ncarr_{i,t-1}$ gives out the number of market participants on a market-time level. $lcconroute_{i,t-1}$ is a quarterly dummy accounting for the existence of a low cost carrier in the market. $CPI_{i,t-1}$ is the *Consumer Price Index* CPI-U. $quarter_t$ is a time dummy to account for time fixed effects. u_{it} represents the error term in this model.

For the last hypothesis, I am going to examine the impact of an entry via a high capacity aircraft on the incumbents' frequency of flights. Because recent research found that the frequency of flights can be a crucial factor to gain a great market share, airlines could respond to an entry by increasing the frequency of flights to set up a unique selling proposition. Therefore, the dependent variable in this regression is the average number of flights per market-time combination whereby the entering airline will be excluded. Like in hypothesis 1 and 2, the main independent variable is the dummy *entry_large* which turns one if an airline enters the market in that particular quarter with a high capacity airplane and zero otherwise. To take market characteristics into account, I am going to control for the Herfindahl index and the number of market participants on a route. Furthermore, a dummy variable controls for the existence of low cost carriers in the market. The consumer price index CPI-U is a control variable for the inflation and time fixed effects are taken into account.

Like in the hypotheses before, I am using the Arellano-Bond estimator. For robustness checks, several combinations of control variables are used. The hypothesis will, analogous to the previous hypotheses, be tested for a high & low market concentration and for less than six and also for six and more market participants. Additionally, I am going to account for the effect resulting from the terroristic attacks in 2001 by conducting the analysis only for the observations before the third quarter in 2001.

The estimated equation is as follows:

$$\begin{aligned}
av\#flights_log_{it} &= \alpha * av\#flights_log_{i,t-1} + ß_0 + ß_1 * entrylarge_{i,t-1} + ß_2 * herfroute_{i,t-1} \\
&+ ß_3 * ncarr_{i,t-1} + ß_4 * lcconroute_{i,t-1} + ß_5 * CPI_{i,t-1} + ß_6 * quarter_t \\
&+ u_{it}
\end{aligned}$$

In this equation $av\#flights\_log_{it}$ describes the natural logarithm of the average number of flights per market and quarter. This variable is also included as a lagged independent variable. The dummy $entrylarge_{i,t-1}$ indicates whether an airline enters the market with a large aircraft in the individual markets per quarter. The variable $herfroute_{i,t-1}$ indicates the Herfindahl index on a particular route for each quarter, $ncarr_{i,t-1}$ gives out the number of participants in the market on a market-time level. The dummy $lcconroute_{i,t-1}$ accounts for the presence of a low cost carrier in the market per individual quarter and $CPI_{i,t-1}$ is the *Consumer Price Index for All Urban Consumers* (CPI-U). Time fixed effects are considered by involving the dummy variable $quarter_t$. u_{it} represents the error term in this model.

Data & Descriptives

This empirical study is mainly based on a dataset which includes 848,637 observations on domestic flights in the United States of America on a quarterly basis from 1993 to 2013. Observations are self-reported by the airlines and collected by the *United States Department of Transportation*.[8] Observed is a total of 54 different carriers (see table A1) whereas 14 of those are low cost carriers. The carriers operate on 5,371 different airport combinations which are defined as markets. To be able to control for additional externalities, the Gross Domestic Product of the USA and the jet fuel price are added to the dataset.[9] The panel in this study is unbalanced due to the non-existence of observations for some airline-time combinations.

The main variables of interest in this study are the capacity per airplane, the airfare per flight and the frequency of flights measured by the number of flights per quarter. The average capacity per airplane for all markets and times is 139 seats per airplane, whereby the dataset also observes flights of comparatively small airplanes with 15 seats and large airplanes with 511 seats (see table 1). The number of passengers transported is on average 99 passengers per flight. The dataset observes empty runs with zero passengers as well as airplanes with 471 passengers on board. On average an airline transported 28,330 passengers on one route per quarter. The maximum number of passengers an airline transported in one market amounts to 307,223 in one quarter. Furthermore, the dataset observes an average of 292 departures which an airline conducts in one market per quarter, whereby the maximum of departures is 3,491 and the minimum 1 departure.

[8] More specifically: United States Department of Transportation - *Research and Innovative Technology Administration (RITA).*

[9] The data on GDP descent from http://www.bea.gov/national/index.htm#gdp and the information on the jet fuel price are obtained from http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=eer_epjk_pf4_rgc_dpg&f=m

Variable (per quarter)	Mean	Std dev	Min	Max
# seats per airplane	139.00	38.19	15	511
# passengers per airplane	98.89	38.58	0	471
# passengers per airline per market	28,329.36	29,824.14	1	307,223
# departures per airline per market	292.38	278.73	1	3,492

Table 1: Descriptive statistics of main variables

Market entries are of particular importance for this study. Within the dataset one can observe 3,913 market entries, thereof are 1,446 low cost carrier entries and 2,467 of legacy carriers (see table 2). In total one can observe 284 market entries of airlines introducing an airline on the market which has at least 1.5 times as many seats as the average on that market.

Observation	Number	Percent of market-airline combination
Market entries	3,913	1.10
Entry of LCC	1,446	0.41
Entry of legacy carrier	2,467	0.70
Entry of large airplane	284	0.08
Number of large airplanes introductions by market participants	53	0.01
Number of different airline-market combination	354,757	100.00

Table 2: Descriptives statistics

The control variables in this dataset include several macroeconomic KPIs and factors which are directly connected to the econometric analysis. Since the jet fuel price is a major cost driver for airlines (see annual report of FY2013, American Airlines), it is included as a control variable in some regressions. In 1999 Q1, the jet fuel price is at its minimum with 0.34 US$ per gallon (see table 3). During the financial crisis in 2008 Q2, the jet fuel price reaches its maximum with 3.66 $US per gallon. Since this study is particularly focused on the change of jet fuel prices, the natural logarithm is used. To account for market concentration, the Herfindahl index is included as a control variable. The lowest value observed is 0.12 and highest 1.00 which indicates a monopoly in this particular market. The economic performance in the USA is observed and included by the absolute Gross Domestic Product as well as the logarithm of it. In 1993 Q1, the GDP accounts for $US 6,748.20 billion, whereas in 2013 Q1 the maximum peaks at $US 16,535.30 billion (see figure 2). This indicator closely resembles the *Consumer Price Index for All Urban Consumers* (see figure 3). Analogous to the GDP, the CPI hast a steady increase and peeks during the financial crisis in 2008.

Variable (per quarter)	Mean	Std. dev.	Min	Max
Jet fuel price (US$/gallon)	1.35	0.94	0.34	3.66
Natural logarithm of Jet fuel price	0.06	0.70	-1.08	1.30
Consumer price index for all urban consumers	185.4474	27.46653	143.1	231.7397
GDP in billion US$	11,605.33	2,960.61	6,748.20	16,535.30
Herfindahl index on route	0.70	0.27	0.12	1.00
Natural logarithm of GDP	9.32	0.27	8.82	9.71
Distance between origin and destination	1,709.83	1,283.52	45.00	9,966.00
Dummy whether there is a low cost airline on the route	0.38	0.49	0.00	1.00

Table 3: Descriptive statistics of control variables

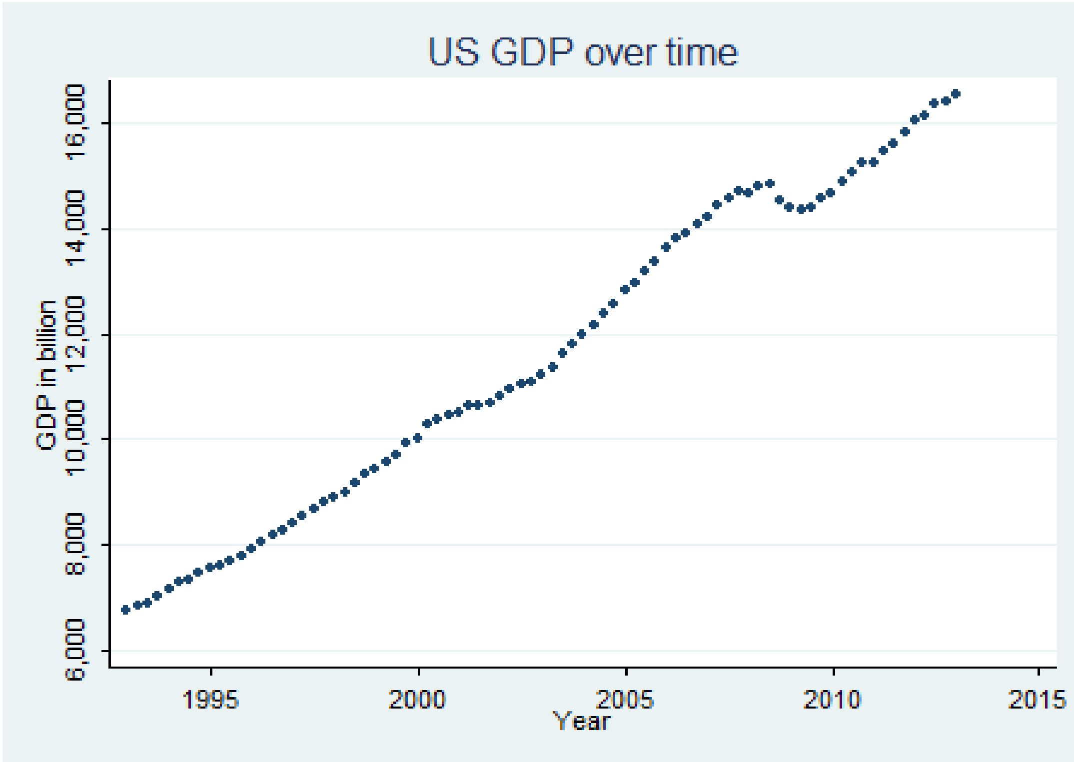

Figure 2: U.S. GPD over time
Source: http://www.bea.gov/national/index.htm#gdp

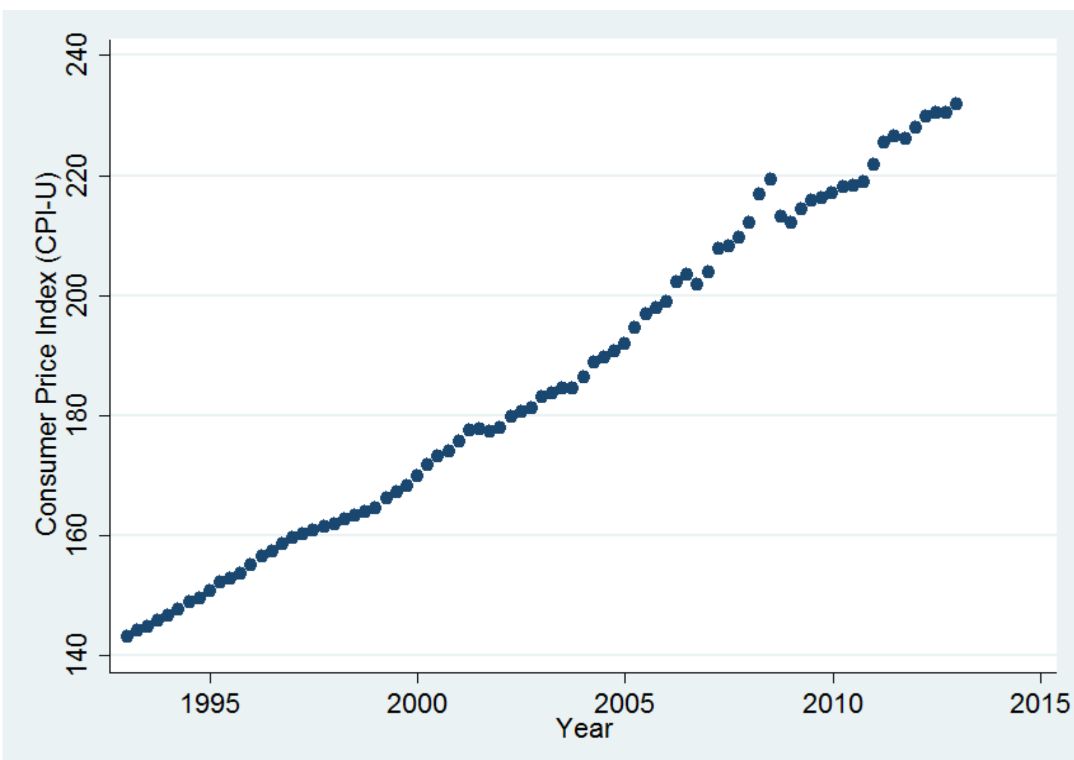

Figure 3: Consumer price index for all urban consumers per quarter
Source: http://www.bls.gov/cpi/cpid1410.pdf

Limitations of this dataset result from the fact that the data is self-reported by the individual airlines.[10] First, there is no superior committee being in charge of the completeness of the data. Second, airlines might not have the incentive to report all the data accurately which would otherwise provide competitors valuable data. By looking at the average number of departures per quarter, one can see that this number is declining from the year 2002 on (see figure 4). This turning point is shortly after the terrorist attacks on the 11th of September in 2001. Two possible theories might explain the decline: First, due to the passenger's fear of further attacks, the aviation sector lost customers. Additionally, the increased costs of higher security standards were apportioned among the customers. This, in turn, led to less traveling customers. Second, due to security issues, airlines might have reported less data. Because this dataset is based on self-reported observations, certain flights might therefore simply not be listed. Due to the reasons mentioned, one could argue that an airline's strategic decision and behavior in the market does not reflect the typical course of action. To take that situation into consideration, I am going to run additional robustness checks for each analysis by taking only from before Q3 2001 into account.

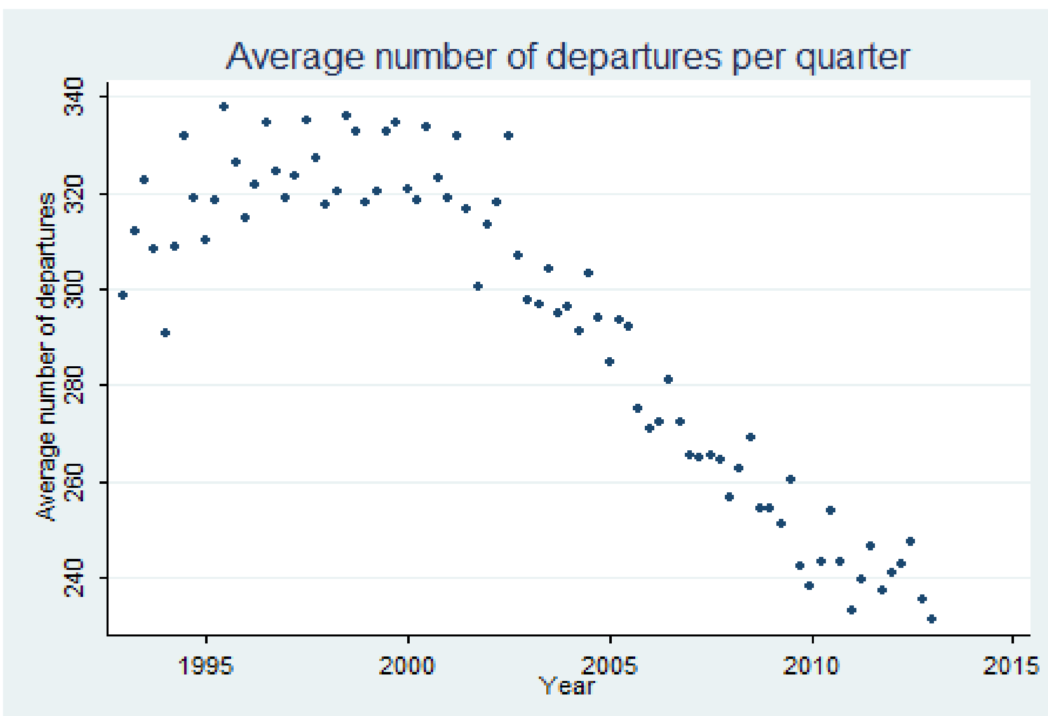

Figure 4: Average number of departures per quarter

[10] On self-reported data also see Brener et al. (2003)

Results

The purpose of this study is to investigate the influence of an airline's high capacity entry on the strategic positioning of incumbent airlines. In the dataset of this analysis, 23 of 54 observed carriers enter a market with a high capacity airplane at some point in time. In total 186 high capacity entries are observed. Chen & Hambrick (1995) find that smaller airlines are more likely to drive an offensive market strategy and attack competitors as compared to larger airlines. Though, the top five airlines with the most high capacity entries are *Delta Airlines* (38 HC entries), *ATA Airlines* (25 HC entries), *American Airlines* (22 HC entries), *United Airlines* (15 HC entries) and *Continental Airlines* (14 HC entries). The fact that these five airlines are not considered to be low cost carriers but major legacy airlines, indicates that costly investments in larger airplanes are primarily done by well-established airlines with a high workload. Additionally, with high capacity aircrafts, airlines are less flexible to adjust the number of seats to the demand. While smaller airlines mostly serve just a few routes, bigger airlines have more options to place a high capacity aircraft on a market with a high demand. Due to seasonal effects the demand might vary and make adjustments necessary.

Hypothesis 1 examines the impact of a market entry via a high capacity airplane on the incumbent's airfare. Expected is a negative contribution of high capacity entries on the incumbent's airfare which is grounded on three suppositions: First, incumbent airlines could try to maintain their market share by gaining additional customers through lower prices. Second, the airfare of entering airlines is lower as compared to the incumbents' fare which could lead to a price competition. Third, in the long term, high capacity airplanes are more cost efficient than smaller ones. This cost advantage could lead the entrant to offer lower airfares which will likewise influence the competitors' airfares. The result of the regression supports this hypothesis. A high capacity market entry is on average associated with a 2.71% decrease of the incumbents' airfares. This result is significant on a 5% level. The control variable n_carr shows that ticket prices decrease, as the number of airlines in the market increase. This could simply be explained by increased competition in the market. The control variable Herfindahl index does not indicate significant results. A negative correlation of 0.7352 between the Herfindahl index and number of competitors in the market might explain this outcome (see table A2). The consumer price index indicates that the average airfare increases slightly with an increasing CPI. This finding is significant on a 0.1% level. The existence of low cost carriers is associated with an increase in ticket prices which goes in line with the theory of Malighetti et al. (2009) who find that low cost carriers do not compete in full service markets. The replacement of CPI by jet fuel price and GDP indicates a significant influence of the jet fuel price on airfares. An increase of jet fuel price by 100% would result in a 4.81% increase of ticket prices. This results is significant on a 0.1% level. Due to a high positive correlation of GDP and jet fuel price, the GDP is omitted from the regression (see table A2).

By regressing the model only for observations in low concentration and high concentration markets, the main independent variable does not indicate significant results. Though, the magnitudes of all independent variables do not change significantly. The results of the regression which is taking only markets with five or less participants into account, support hypothesis 1, likewise. By excluding markets with five or less participants, no significant results can be estimated. Furthermore, hypothesis 1 can be supported by investigating the data before September 11th in 2001. The coefficient of the dummy variable indicating high capacity entries is significant on a 1% level and its magnitude is even higher as compared to the base model.

Hypothesis 2 investigates the incumbents' capacity adjustments in reaction to market entries via high capacity airplanes. Because larger airplanes are supposed to entail significant cost advantages, incumbent airlines are expected to follow the strategy of realizing economies of scale through higher capacities. This hypothesis cannot be supported through the base model. The magnitude of dummy variable entry_large has the expected positive sign, though, this finding is not significant on a 5% level. By looking at the regressions for different market segments, one can observe that in markets with five or more participants, the entry of an airline with a high capacity airplane induces incumbents to decrease their capacity. This finding is significant on a 0.1% level. The negative sign could be explained by a possible oversupply of seats. Since the supply of flights in markets with five or more participants is already high, the additional high capacity airplane might lead to an oversupply of seats. An under-utilization of airplanes is especially due to high fixed costs in the aviation sector not lucrative. Analogous to the base model, the regressions for high concentration and low concentration markets do not indicate significant results. The Analysis which is taking only data from Q1 1993 to Q2 2001 into account, however, suggests that incumbents decrease their average capacity when an additional carrier enters the market. Since passenger numbers decreased after Q2 in 2001 due to concerns about the safety of flights, airlines were expected to adjust their fleet planning under exceptional circumstances. This means that an analysis depicts a more realistic outcome for capacity adjustments when taking into account data from quarters before 9/11. For observations after 9/11 it is difficult to determine whether capacity adjustments are caused by market entries or consequences from the terroristic attacks.

The control variables in the base model indicate that in markets with a high market concentration airlines are more likely to deploy airplanes of a smaller capacity compared to less concentrated markets. However, in markets where a LCC is present, the average aircraft size is slightly greater than in markets without LCCs. The consumer price index does not have an effect on the aircraft capacity.

In hypothesis 3, I am going to look at the frequency of incumbents and to what extent it is affected by the airplane capacity of an entering airline. Following the theory, through the existence of an S-curve effect incumbents could increase their frequency to maintain market power. In this analysis, the base model cannot support or reject this hypothesis due to missing significance. Though, by taking only markets with a low concentration and markets with more than five participants into account, the results are significant on a 1% level and suggest a decrease in frequency when an airline enters the market with a high capacity airplane. A possible explanation might be the oversupply of seats which induces airlines to avoid spare seats. The effects of the S-curve effect can therefore not be supported by this study. However, by looking at control variables I find that a high market concentration and high number of market participants, however, seem to induce airlines to increase their frequency. Like expected in the analysis before, the replacement of CPI by the jet fuel price and GDP shows that an increase in jet fuel price is followed by a decrease in frequency. This hints at a higher efficiency of larger airplanes. Like before, GDP is omitted due to a high positive correlation with the jet fuel price.

	(1)	(2)	(3)
	H1 base model Natural logarithm of the incumbents' average airfare	H2 base model Natural logarithm of the incumbents' average capacity	H3 base model Natural logarithm of the incumbents' average frequency
Lagged dependent variable	0.4422*** (0.01)	0.5329*** (0.01)	0.0165* (0.01)
Dummy variable high capacity entry	-0.0271* (0.01)	0.0024 (0.01)	-0.0370 (0.02)
Herfindahl index on route	-0.0089 (0.01)	-0.0182*** (0.00)	0.0751*** (0.02)
Number of carriers on the Market	-0.0019*** (0.00)	-0.0026*** (0.00)	0.0223*** (0.00)
Dummy variable for the existence of a LCC in the Market	0.0115*** (0.00)	0.0032* (0.00)	0.0630*** (0.01)
Consumer price index	0.0014*** (0.00)	-0.0000 (0.00)	-0.0137*** (0.00)
Constant	2.6110*** (0.04)	2.3197*** (0.04)	7.7084*** (0.09)
Observations	188663	188910	188910

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Regression output for main models

The sensitivity analysis partly supports the findings of the previous regressions and indicates stronger effects for larger airplanes. Shifting the definition of high capacity airplanes from larger than 150% of the average airplane size in the market to 175% decreases the magnitude of the main independent variable in hypothesis 1 from -0.0271 to -0.0319 which means that the effect of entries via larger airplanes is stronger by 0.48 percentage points. By defining high capacity airplanes as being larger than 125% of the average airplane size in the market, the magnitude decreases to -0.0142 but no significant results can be estimated. This could suggest that an airplane being 25% larger than the average, is not perceived as a high capacity airplane. By looking at the regressions of hypothesis 2, the sensitivity analysis suggests a stronger impact of larger high capacity airplanes on the incumbents' average capacity as compared to smaller ones. Though, like in the base model, these findings are not significant. The same holds for the sensitivity analyses of hypothesis 3. The magnitude indicates stronger effects for larger airplanes, but these findings are insignificant, too.

The Wald Chi-Square statistic is used to test the goodness of fit. Its null hypothesis states that all regression coefficients in the model are simultaneously equal to zero. This hypothesis can be rejected which means that at least one regression coefficient is different to zero. To test for over-identification of the Arellano-Bond model, I am going to conduct a Sargan test. In the first instance the test indicates to reject the null hypothesis "overidentifying restrictions are valid" which could be a sign for an over-identified model. Though, like mentioned by Chao at al. (2014), this test is not robust to large numbers of instruments. For instance, the model testing hypothesis 1 features 394 instruments which challenges the significance of this test and does not allow conclusions. The Arellano-Bond test for autocorrelation rejects the second order null hypothesis, indicating the non-existence of autocorrelation in first differenced error terms. Like expected by Roodman (2009a), the null hypothesis of the first order in this type of model is rejected. Though, this does not support any conclusions.

	(1)	(2)	(3)	(4)	(5)	(6)
	H1 - 125% Natural logarithm of the incumbents' average airfare	H1 - 175% Natural logarithm of the incumbents' average airfare	H2 - 125% Natural logarithm of the competitors' average capacity	H2 - 175% Natural logarithm of the competitors' average capacity	H3 - 125% Natural logarithm of the incumbents' average frequency	H3 - 175% Natural logarithm of the incumbents' average frequency
Lagged dependent Variable	0.4454***	0.4430***	0.5390***	0.5278***	0.0116	0.0159*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dummy variable high capacity entry	-0.0142	-0.0319*	0.0011	0.0019	-0.0190	-0.0389
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Herfindahl index on Route	0.0090	-0.0091	-0.0196***	-0.0179***	0.0720***	0.0736***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)
Number of carriers on the Market	-0.0020***	-0.0019***	-0.0024***	-0.026***	0.0211***	0.0226***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Dummy variable for the existence of a LCC in the Market	-0.0102***	-0.0115***	0.0040**	-0.0028***	0.0637***	0.0625***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Consumer price index	0.0014***	0.0014***	-0.0000	-0.0000	-0.0137***	-0.0137***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)	(0.03)
Constant	2.5948***	2.6055***	2.3465***	2.3465***	7.7308***	7.7104***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.09)	(0.09)
Observations	186725	189296	187312	189362	187312	189362

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Regression output for sensitivity analysis

Conclusion

Previous research finds that three main factors influence an airline's market share: The frequency of flights, airfare and capacity of airplanes. This empirical analysis investigates how incumbent airlines change their strategy when new airlines enter markets with high capacity airplanes. From the investigation of hypothesis 1 we learn that the entry of high capacity airplanes induces incumbents to decrease their airfare by on average 3%. This finding supports the study of Joskow et al. (1994) saying that the additional supply of seats on a route through a market entry lets incumbents decrease airfares. A sensitivity analysis additionally reveals that this effect is stronger for larger airplanes.

Next to adjustments in airfare, previous research suggests changes in frequency of flights or airplane capacity in reaction to changing market conditions. In particular, the analysis on hypothesis 2 investigates the impact of high capacity market entries on the incumbents' airplane capacity. By analyzing the output of the base model, no significant conclusions can be drawn. Though, the exclusion of markets with five or less participants indicates that a high capacity market entry leads incumbent airlines to decrease their average number of seats per airplane. On average, in reaction to a high capacity market entry, incumbent airlines decrease their number of seats per airplane by 2.31%. Whereas some previous studies suggest a positive sign, other studies explain the negative contribution by stating that especially in markets with numerous competitors a possible oversupply of seats induces airlines to decrease their capacity slightly to avoid spare seats. Especially due to a high cost sensitivity excess capacity seems to be unprofitable. The investigation of hypothesis 3 examines changes of frequency in reaction to high capacity market entries. The results suggest that especially in low concentrated markets and markets with more than five market participants, airlines tend to decrease their frequency in response to high capacity market entries. On average, incumbent airlines reduce the frequency of flights by roughly 8%.

The combination of hypothesis 2 and 3 shows that airlines decrease their overall capacity which is the product of airplane capacity times frequency in reaction to high capacity entries. With this, a high capacity entry seems to have a greater impact on frequency as compared to airplane capacity.

This can be explained by the fact that mutations in frequency are more reversible decisions as compared to mutations in the number of seats per airplane. Furthermore, frequency adjustments seem to be easier and faster to implement as compared to fleet adjustments. The process of code sharing might here be a common means. With this, two airlines which offer flights on the same route, have the option to conduct one flight commonly whereby the other flight is cancelled. It seems obvious that this strategy turns out to be more cost-effective. Combining this insight with the results of hypothesis 1, one could conclude that a high capacity market entry represents a challenge for incumbent airlines which deal with the upcoming threat by entering a price competition and improving (cost-)efficiency primarily through adjustments in frequency.

Limitations and future research

Although this research provides a grounded analysis, it has some limitations which could be eliminated by further detailed analyses: Like mentioned above, Pai (2010) finds that the target group an airlines serves, has a significant impact on the frequency of flights. An increase of the proportion of passengers with a managerial position will lead the airline to offer a higher frequency of flights with airplanes of a lower capacity. He mentions that this effect is caused by a higher time sensitivity of managers. However, airplanes transporting leisure travelers are more likely to be larger and scheduled with a lower frequency. By adding passenger characteristics which distinguish between e.g. leisure & business travelers or low cost & premium passengers, the analysis' validity could be enhanced. The distinction between smaller and larger airlines could likewise provide further insights. Like Chen & Hambrick (1995) find, substantial difference between smaller and larger firms can be found by looking at strategy adjustments.

Furthermore, this master's thesis focuses on capacity in terms of seat quantity per aircraft and frequency of flights. To observe changes in the airplane's number of seats might not be optimal since stepless adjustments are not feasible for airlines. Because standard airplanes are used on many routes, airlines might not be able to conduct fine adjustments to market conditions. The costs of changing to a different aircraft type probably outweigh cost optimization through a higher load factor. An analysis which investigates capacity in terms of fleet size is also imaginable. By increasing capacity through adding smaller airplanes to the fleet, an airline might face higher investment costs per seat but might also increase the fleet's flexibility at the same time. Depending on market characteristics, an increase in the number of aircrafts rather than in an aircraft's size might optimize utility. Future research could take this into account.

With respect to the methodology used, a dynamic panel data model seems to be the best tool to observe strategic decisions in multiple markets over time. Nevertheless, the use of panel data requires one single observation per panel-time combination which makes it necessary to average observed variables among airlines. This way, the variation between airlines is lost in this study.

Though, a concentrated analysis on only one market or one airline would lead to less representative results.

Finally, for airlines facing capacity related issues, this research provides useful insights. Though, to what extent airplane capacity is available for airlines, depends inter alia on aircraft manufacturer like Airbus or Boeing. Future research should be done on airplane capacity with respect to demand for capacity. It might be valuable for manufacturers to predict the market’s need for larger or smaller airplanes since the direction of their strategic focus is a long term decision due to high engineering efforts.

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Appendix

IATA	Airline & time of operation	Type
AA	American Airlines Inc. (1960 -)	Legacy carrier
AS	Alaska Airlines Inc. (1960 -)	Legacy carrier
DL	Delta Air Lines Inc. (1960 -)	Legacy carrier
HA	Hawaiian Airlines Inc. (1960 -)	Legacy carrier
NK	Spirit Air Lines (1992 -)	Low cost carrier
QX	Horizon Air (1984 -)	Legacy carrier
UA	United Air Lines Inc. (1960 -)	Legacy carrier
US	US Airways Inc. (1997 -)	Legacy carrier
WN	Southwest Airlines Co. (1979 -)	Low cost carrier
EV	ExpressJet Airlines Inc. (2012 -)	Legacy carrier
CO	Continental Air Lines Inc. (1960 - 2011)	Legacy carrier
F9	Frontier Airlines Inc. (1994 -)	Low cost carrier
FL	Frontier Airlines Inc. (1960 - 1986)	Legacy carrier
SY	Sun Country Airlines d/b/a MN Airlines (2005 -)	Low cost carrier
CS	Continental Micronesia (1993 - 2010)	Legacy carrier
NW	Northwest Airlines Inc. (1960 - 2009)	Legacy carrier
TZ	ATA Airlines d/b/a ATA (2003 - 2008)	Legacy carrier
HP	America West Airlines Inc. (1983 - 2007)	Legacy carrier
XJ	Mesaba Airlines (1997 - 2011)	Legacy carrier
ZW	Air Wisconsin Inc. (1979 - 1993)	Legacy carrier
B6	JetBlue Airways (2000 -)	Low cost carrier
G4	Allegiant Air (2000 -)	Low cost carrier
YV	Mesa Airlines Inc. (1995 -)	Legacy carrier
9E	Pinnacle Airlines Inc. (2002 - 2013)	Legacy carrier
RP	Chautauqua Airlines Inc. (2004 -)	Legacy carrier
U5	USA 3000 Airlines (2003 - 2012)	Low cost carrier
TW	Trans World Airways LLC (2001 - 2001)	Legacy carrier
NJ	Vanguard Airlines Inc. (1994 - 2002)	Low cost carrier
YX	Midwest Airline, Inc. (2003 - 2009)	Legacy carrier
FF	Tower Air Inc. (1983 - 2000)	Low cost carrier
QQ	Reno Air Inc. (1992 - 1999)	Legacy carrier
U2	UFS Inc. (1993 - 2000)	Legacy carrier
KP	Kiwi International (1992 - 2000)	Legacy carrier
NA	North American Airlines (2005 -)	Legacy carrier
RV	Reeve Aleutian Airways Inc. (1960 - 2002)	Legacy carrier
VX	Virgin America (2007 -)	Low cost carrier
KW	Pacific Interstate Airlines (1989 - 1991)	Legacy carrier

PN	Pan American Airways Corp. (1999 - 2004)	Legacy carrier
J7	Valujet Airlines Inc. (1993 - 2000)	Low cost carrier
W9	Eastwind Airlines Inc. (1995 - 1999)	Legacy carrier
N7	National Airlines (1999 - 2002)	Low cost carrier
DH	Atlantic Coast Airlines (2002 - 2004)	Legacy carrier
P9	Pro Air Inc. (1997 - 2000)	Legacy carrier
BF	Markair Inc. (1984 - 1995)	Legacy carrier
W7	Western Pacific Airlines (1995 - 1998)	Low cost carrier
E9	Boston-Maine Airways (2003 - 2008)	Legacy carrier
KN	Morris Air Corporation (1992 - 1994)	Legacy carrier
XE	ExpressJet Airlines Inc. (2006 - 2011)	Legacy carrier
RL	UltrAir (1993 - 1994)	Legacy carrier
T3	Tristar Airlines Inc. (1995 - 1997)	Legacy carrier
QD	Grand Airways Inc. (1995 - 1995)	Legacy carrier
SX	Aeroejecutivo S.A. (1997 - 2000)	Low cost carrier
ZA	Accessair Holdings (1998 - 2002)	Legacy carrier
OE	Westair Airlines Inc. (1988 - 1993)	Legacy carrier

Table A1: Airlines observed in this dataset

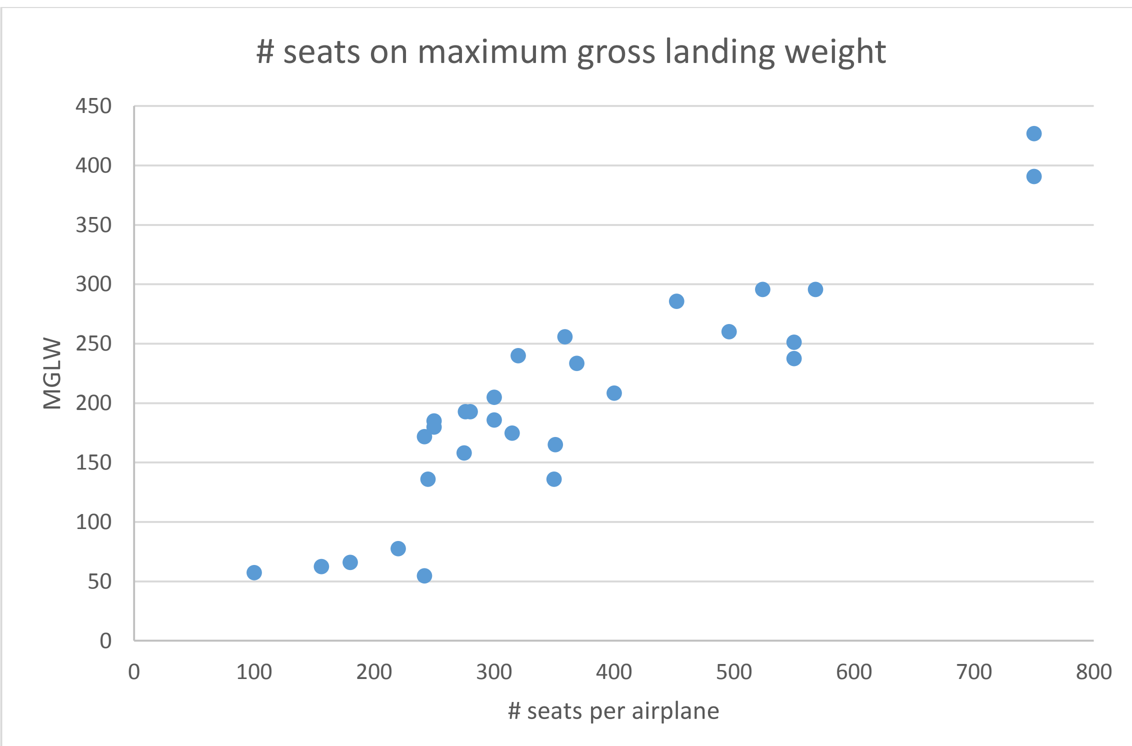

Figure A1: Relation of the number of seats on the maximum gross landing weight for the major airplanes in the passenger aviation sector

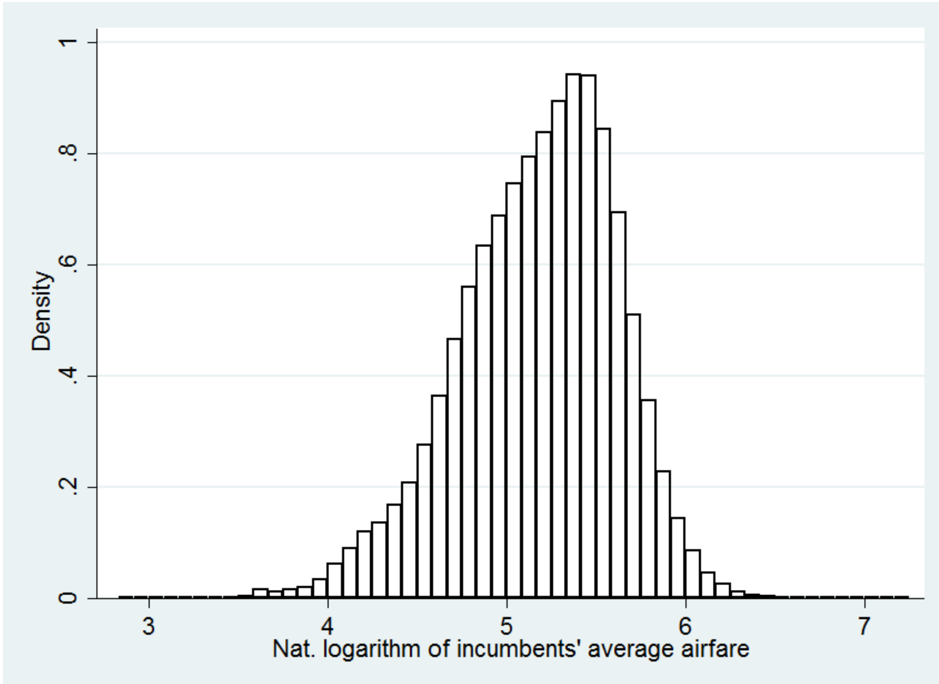

Figure A2: Distribution of the natural logarithm of the incumbents' average airfare

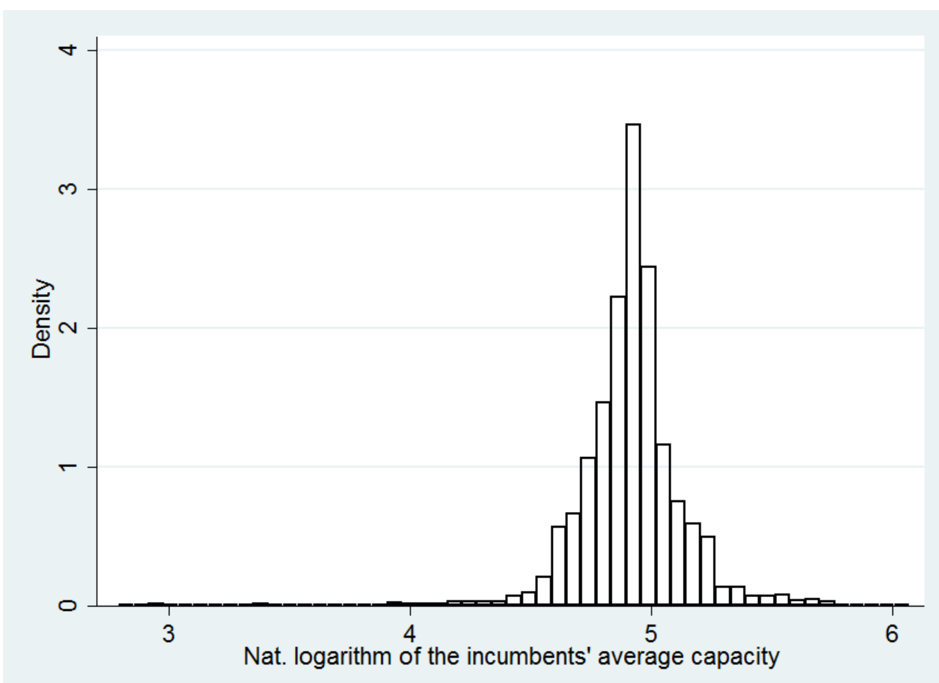

Figure A3: Distribution of the natural logarithm of the incumbents' average capacity

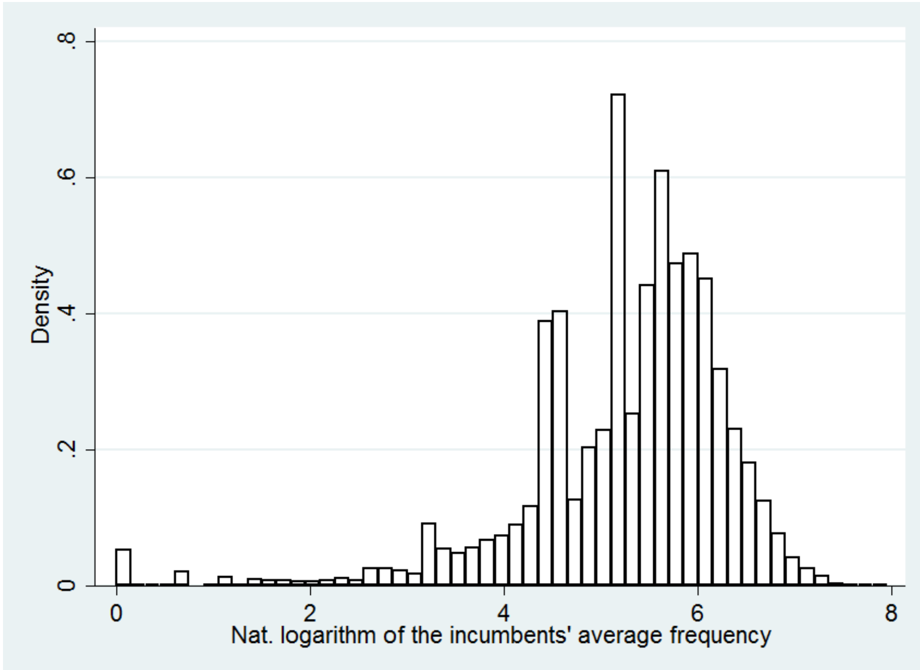

Figure A4: Distribution of the natural logarithm of the incumbents' average frequency

	Natural logarithm of the incumbents' average airfare	Dummy variable high capacity entry	Herfindahl Index on route	Number of carriers on the market	Dummy variable for the existence of a LCC	Natural logarithm of GDP	Natural logarithm of jet fuel price	Consumer price index for all urban consumers
Natural logarithm of the incumbents' average airfare	1							
Dummy variable high capacity entry	-0.0009	1						
Herfindahl Index on route	0.1554	-0.0056	1					
Number of carriers on the market	-0.1418	0.0152	-0.7352	1				
Dummy variable for the existence of a LCC	-0.391	-0.0009	-0.1926	0.2	1			
Natural logarithm of GDP	0.0753	-0.0217	-0.1476	0.2148	0.3496	1		
Natural logarithm of jet fuel price	0.0656	-0.017	-0.1382	0.2116	0.3462	0.9179	1	
Consumer price index for all urban consumers	0.0668	-0.02	-0.1303	0.2051	0.3724	0.9844	0.9468	1

Table A2: Correlation Table

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_incumbents_logged	0.4421***	0.4415***	0.4415***	0.4422***	0.4422***	0.4422***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0273*	-0.0272*	-0.0264*	-0.0271*	-0.0271*	-0.0271*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0066	-0.0109	-0.0089	-0.0089	-0.0089
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0013**	-0.0019***	-0.0019***	-0.0019***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0115***	0.0115***	0.0115***
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0481***	
					(0.00)	
L. CPIU						0.0014***
						(0.00)
Constant	2.8474***	2.8548***	2.8617***	2.9242***	2.9388***	2.6110***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	188663	188663	188663	188663	188663	188663

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: H1_BASEMODEL

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_incumbents_logged	0.3878***	0.3879***	0.3880***	0.3881***	0.3881***	0.3881***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0265	-0.0264	-0.0256	-0.0257	-0.0257	-0.0257
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. herf_route		-0.0012	-0.0092	-0.0081	-0.0081	-0.0081
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. n_carr			-0.0009	-0.0011	-0.0011	-0.0011
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0039	0.0039	0.0039
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0389***	
					(0.00)	
L. CPIU						0.0016***
						(0.00)
Constant	3.1370***	3.1375***	3.1461***	3.1830***	3.2527***	2.8768***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Observations	98332	98332	98332	98332	98332	98332

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: H1_HIGH_CONCENTRATION

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_incumbents_logged	0.4625***	0.4641***	0.4639***	0.4657***	0.4657***	0.4657***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0127	-0.0124	-0.0109	-0.0135	-0.0135	-0.0135
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. herf_route		-0.0277	-0.0387*	-0.0367*	-0.0367*	-0.0367*
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. n_carr			-0.0022***	-0.0028***	-0.0028***	-0.0028***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0163***	0.0163***	0.0163***
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0195***	
					(0.00)	
L. CPIU						0.0025***
						(0.00)
Constant	2.6493***	2.6569***	2.7665***	2.7525***	2.7486***	2.3033***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	76153	76153	76153	76153	76153	76153

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: H1_LOW_CONCENTRATION

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_incumbents_logged	0.1023***	0.1034***	0.0999***	0.1011***	0.1120***	0.1144***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. entry_large	-0.0057	-0.0120	-0.0091	-0.0057	-0.0178	-0.0117
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		0.1789***	0.1772***	0.1772***	0.1826***	0.1905***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. n_carr			-0.0005	-0.0008	-0.0010	-0.0010
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0140***	0.0154***	0.0151***
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0981***	
					(0.02)	
L. CPIU						0.0057***
						(0.00)
Constant	4.4421***	4.3386***	4.3637***	4.3574***	4.3561***	3.2658***
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.15)
Observations	5430	5430	5430	5430	5430	5430

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: H1_ PARTICIPANTS_ABOVE_5

	(1) average_fare_incu mbents_logged	(2) average_fare_incu mbents_logged	(3) average_fare_incu mbents_logged	(4) average_fare_incu mbents_logged	(5) average_fare_incu mbents_logged	(6) average_fare_incu mbents_logged
L. average_fare_incumbents_logged	0.4319***	0.4314***	0.4312***	0.4316***	0.4316***	0.4316***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0325**	-0.0326**	-0.0312*	-0.0314*	-0.0314*	-0.0314*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0072	-0.0127	-0.0113	-0.0113	-0.0113
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0019**	-0.0023***	-0.0023***	-0.0023***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0079**	0.0079**	0.0079**
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0510***	
					(0.00)	
L. CPIU						0.0015***
						(0.00)
Constant	2.9839***	2.9916***	3.0008***	2.9963***	3.0079***	2.6727***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	171595	171595	171595	171595	171595	171595

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: H1_PARTICIPANTS_BELOW_6

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_incumbents_logged	0.4615***	0.4609***	0.4605***	0.4611***	0.4611***	0.4611***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0370**	-0.0370**	-0.0355**	-0.0361**	-0.0361**	-0.0361**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0093	-0.0156	-0.0142	-0.0142	-0.0142
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0021*	-0.0025*	-0.0025*	-0.0025*
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0071	0.0071	0.0071
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.1045***	
					(0.00)	
L. CPIU						0.0021***
						(0.00)
Constant	2.8036***	2.8140***	2.8251***	2.8207***	2.9392***	2.4472***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Observations	80938	80938	80938	80938	80938	80938

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: H1_BASEMODEL_BEFORE_9_11

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.5300^{***}	0.5298^{***}	0.5327^{***}	0.5329^{***}	0.5329^{***}	0.5329^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	0.0011	0.0008	0.0027	0.0024	0.0024	0.0024
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0107^{***}	-0.0189^{***}	-0.0182^{***}	-0.0182^{***}	-0.0182^{***}
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L. n_carr			-0.0024^{***}	-0.0026^{***}	-0.0026^{***}	-0.0026^{***}
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0032^{*}	0.0032^{*}	0.0032^{*}
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					-0.0016	
					(0.00)	
L. CPIU						-0.0000
						(0.00)
Constant	2.3097^{***}	2.3180^{***}	2.3165^{***}	2.3143^{***}	2.3173^{***}	2.3197^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	188910	188910	188910	188910	188910	188910

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: H2_BASEMODEL

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.5425***	0.5438***	0.5457***	0.5457***	0.5457***	0.5457***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	0.0081	0.0085	0.0097	0.0096	0.0096	0.0096
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		0.0400***	0.0281*	0.0284*	0.0284*	0.0284*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0014*	-0.0014*	-0.0014*	-0.0014*
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0001	0.0001	0.0001
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0015	
					(0.00)	
L. CPIU						0.0000
						(0.00)
Constant	2.2489***	2.2040***	2.2058***	2.2055***	2.2086***	2.2009***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	98345	98345	98345	98345	98345	98345

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: H2_HIGH_CONCENTRATION

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.4814***	0.4820***	0.4846***	0.4854***	0.4854***	0.4854***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0022	-0.0021	-0.0004	-0.0007	-0.0007	-0.0007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		0.0054	-0.0062	-0.0056	-0.0056	-0.0056
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0024***	-0.0025***	-0.0025***	-0.0025***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0043**	0.0043**	0.0043**
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					-0.0080***	
					(0.00)	
L. CPIU						-0.0002***
						(0.00)
Constant	2.5566***	2.5505***	2.5507***	2.5452***	2.5399***	2.5877***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Observations	76321	76321	76321	76321	76321	76321

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: H2_LOW_CONCENTRATION

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.2044***	0.2038***	0.1850***	0.2050***	0.1932***	0.2086***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0234***	-0.0241***	-0.0237***	-0.0236***	-0.0243***	-0.0231***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L. herf_route		0.0271*	0.0243*	0.0207	0.0232	0.0205
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0019***	-0.0020***	-0.0021***	-0.0020***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0032	0.0035*	0.0034
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					-0.0079	
					(0.01)	
L. CPIU						-0.0020***
						(0.00)
Constant	3.9076***	3.9036***	4.0115***	3.9168***	3.9658***	4.4014***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.11)
Observations	5431	5431	5431	5431	5431	5431

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: H2_MARKET_PARTICIPANTS_ABOVE_5

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.5539***	0.5538***	0.5565***	0.5568***	0.5568***	0.5568***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	0.0065	0.0061	0.0083	0.0081	0.0081	0.0081
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0132***	-0.0211***	-0.0206***	-0.0206***	-0.0206***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L. n_carr			-0.0025***	-0.0027***	-0.0027***	-0.0027***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0031	0.0031	0.0031
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					-0.0028*	
					(0.00)	
L. CPIU						-0.0000
						(0.00)
Constant	2.1876***	2.1974***	2.2009***	2.1935***	2.2016***	2.2081***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	171823	171823	171823	171823	171823	171823

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: H2_PARTICIPANTS_BELOW_6

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.5608***	0.5608***	0.5632***	0.5638***	0.5638***	0.5638***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0251***	-0.0339***	-0.0322***	-0.0322***	-0.0322***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0030***	-0.0033***	-0.0033***	-0.0033***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0081**	0.0081**	0.0081**
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					-0.0047**	
					(0.00)	
L. CPIU						-0.0002*
						(0.00)
Constant	2.1489***	2.1692***	2.1702***	2.1593***	2.1603***	2.1879***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Observations	80959	80959	80959	80959	80959	80959

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A14: H2_BASEMODEL_BEFORE_9_11

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_incumbents_logged	0.0076	0.0079	0.0150*	0.0165*	0.0165*	0.0165*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0173	-0.0176	-0.0336	-0.0370	-0.0370	-0.0370
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. herf_route		-0.0187	0.0627***	0.0751***	0.0751***	0.0751***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. n_carr			0.0249***	0.0223***	0.0223***	0.0223***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0630***	0.0630***	0.0630***
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.3187***	
					(0.01)	
L. CPIU						-0.0137***
						(0.00)
Constant	4.8641***	4.8976***	4.7282***	4.6980***	5.2003***	7.7084***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
Observations	188910	188910	188910	188910	188910	188910

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A15: H3_BASEMODEL

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_incumbents_logged	-0.0295***	-0.0279***	-0.0231**	-0.0205*	-0.0205*	-0.0205*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	0.0116	0.0099	-0.0110	-0.0102	-0.0102	-0.0102
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. herf_route		-0.1397**	0.1125*	0.1405**	0.1405**	0.1405**
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
L. n_carr			0.0294***	0.0251***	0.0251***	0.0251***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0810***	0.0810***	0.0810***
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.3016***	
					(0.02)	
L. CPIU						-0.0146***
						(0.00)
Constant	5.3144***	5.4410***	5.1253***	4.9844***	5.1414***	7.8800***
	(0.05)	(0.06)	(0.07)	(0.07)	(0.07)	(0.13)
Observations	98345	98345	98345	98345	98345	98345

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A16: H3_HIGH_CONCENTRATION

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_incumbents_logged	0.0732***	0.0716***	0.0925***	0.0943***	0.0943***	0.0943***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0690*	-0.0684*	-0.0834**	-0.0889**	-0.0889**	-0.0889**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. herf_route		0.0769**	0.1965***	0.2035***	0.2035***	0.2035***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. n_carr			0.0249***	0.0231***	0.0231***	0.0231***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0559***	0.0559***	0.0559***
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.2700***	
					(0.01)	
L. CPIU						-0.0109***
						(0.00)
Constant	5.4495***	5.4170***	5.2170***	5.1889***	4.8792***	6.7615***
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.12)
Observations	76321	76321	76321	76321	76321	76321

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A17: H3_LOW_CONCENTRATION

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_incumbents_logged	0.0478***	0.0430**	0.0694***	0.0473**	0.0550***	0.0482**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
L. entry_large	-0.0376*	-0.0341*	-0.0490**	-0.0552***	-0.0431*	-0.0454**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
L. herf_route		-0.1313*	-0.0793	-0.0647	-0.0863	-0.0744
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
L. n_carr			0.0140***	0.0131***	0.0131***	0.0129***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0098	0.0081	0.0088
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.1995***	
					(0.04)	
L. CPIU						-0.0086***
						(0.00)
Constant	5.7786***	5.8682***	5.5641***	5.7369***	5.5858***	6.8020***
	(0.12)	(0.12)	(0.10)	(0.13)	(0.11)	(0.28)
Observations	5431	5431	5431	5431	5431	5431

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A18: H3_PARTICIPANTS_ABOVE_5

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_incumbents_logged	0.0003	0.0006	0.0069	0.0079	0.0079	0.0079
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0021	-0.0026	-0.0226	-0.0249	-0.0249	-0.0249
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. herf_route		-0.0227	0.0697^{***}	0.0840^{***}	0.0840^{***}	0.0840^{***}
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. n_carr			0.0310^{***}	0.0274^{***}	0.0274^{***}	0.0274^{***}
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0727^{***}	0.0727^{***}	0.0727^{***}
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.3342^{***}	
					(0.01)	
L. CPIU						-0.0143^{***}
						(0.00)
Constant	4.8557^{***}	4.8695^{***}	4.6721^{***}	4.6615^{***}	5.1855^{***}	7.7996^{***}
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.10)
Observations	171823	171823	171823	171823	171823	171823

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A19: H3_PARTICIPANTS_BELOW_6

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_ incumbents_logged	0.0761***	0.0754***	0.0865***	0.0855***	0.0855***	0.0855***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0058	-0.0075	-0.0325	-0.0393	-0.0393	-0.0393
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. herf_route		-0.1069***	0.0009	0.0213	0.0213	0.0213
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
L. n_carr			0.0372***	0.0327***	0.0327***	0.0327***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0897***	0.0897***	0.0897***
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.0684***	
					(0.01)	
L. CPIU						-0.0065***
						(0.00)
Constant	5.0794***	5.1704***	4.9514***	4.8993***	4.8536***	6.0428***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.13)
Observations	80959	80959	80959	80959	80959	80959

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A20: H3_BEFORE_9_11

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_ incumbents_logged	0.4453***	0.4447***	0.4447***	0.4454***	0.4454***	0.4454***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0146*	-0.0146*	-0.0136	-0.0142	-0.0142	-0.0142
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0060	-0.0107	-0.0090	-0.0090	-0.0090
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0015**	-0.0020***	-0.0020***	-0.0020***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0102***	0.0102***	0.0102***
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					0.0487***	
					(0.00)	
L. CPIU						0.0014***
						(0.00)
Constant	2.8313***	2.8379***	2.8455***	2.9070***	2.9223***	2.5948***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	186725	186725	186725	186725	186725	186725

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A21: H1_BASEMODEL_ Sensitivity analysis 125%

	(1) average_fare_incumbents_logged	(2) average_fare_incumbents_logged	(3) average_fare_incumbents_logged	(4) average_fare_incumbents_logged	(5) average_fare_incumbents_logged	(6) average_fare_incumbents_logged
L. average_fare_ incumbents_logged	0.4429***	0.4423***	0.4423***	0.4430***	0.4430***	0.4430***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0315*	-0.0314*	-0.0305*	-0.0319*	-0.0319*	-0.0319*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0069	-0.0112	-0.0091	-0.0091	-0.0091
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. n_carr			-0.0013**	-0.0019***	-0.0019***	-0.0019***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0115***	0.0115***	0.0115***
				(0.00)	(0.00)	(0.00)
L. fuel_price _logged					0.0482***	
					(0.00)	
L. CPIU						0.0014***
						(0.00)
Constant	2.8431***	2.8507***	2.8578***	2.8503***	2.9351***	2.6055***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	189296	189296	189296	189296	189296	189296

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A22: H1_BSEMODEL_Sensitivity analysis 175%

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_ incumbents_logged	0.5366*** (0.01)	0.5361*** (0.01)	0.5387*** (0.01)	0.5390*** (0.01)	0.5390*** (0.01)	0.5390*** (0.01)
L. entry_large	-0.0000 (0.00)	-0.0004 (0.00)	0.0013 (0.00)	0.0011 (0.00)	0.0011 (0.00)	0.0011 (0.00)
L. herf_route		-0.0130*** (0.00)	-0.0204*** (0.00)	-0.0196*** (0.00)	-0.0196*** (0.00)	-0.0196*** (0.00)
L. n_carr			-0.0022*** (0.00)	-0.0024*** (0.00)	-0.0024*** (0.00)	-0.0024*** (0.00)
L. lcc_on_route				0.0040** (0.00)	0.0040** (0.00)	0.0040** (0.00)
L. fuel_price_logged					-0.0015 (0.00)	
L. CPIU						-0.0000 (0.00)
Constant	2.2746*** (0.04)	2.2880*** (0.04)	2.2844*** (0.04)	2.2812*** (0.04)	2.2859*** (0.04)	2.2903*** (0.04)
Observations	187312	187312	187312	187312	187312	187312

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A23: H2_BASEMODEL_Sensitivity analysis 125%

	(1) av_cap_incumbents_logged	(2) av_cap_incumbents_logged	(3) av_cap_incumbents_logged	(4) av_cap_incumbents_logged	(5) av_cap_incumbents_logged	(6) av_cap_incumbents_logged
L.av_cap_incumbents_logged	0.5246***	0.5244***	0.5277***	0.5278***	0.5278***	0.5278***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	0.0008	0.0006	0.0023	0.0019	0.0019	0.0019
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0102**	-0.0184***	-0.0179***	-0.0179***	-0.0179***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L. n_carr			-0.0025***	-0.0026***	-0.0026***	-0.0026***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0028	0.0028	0.0028
				(0.00)	(0.00)	(0.00)
L. fuel_price_logged					-0.0018	
					(0.00)	
L. CPIU						-0.0000
						(0.00)
Constant	2.3333***	2.3435***	2.3404***	2.3385***	2.3422***	2.3465***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	189362	189362	189362	189362	189362	189362

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A24: H2_BASEMODEL_Sensitivity analysis 175%

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_ incumbents_logged	0.0036	0.0038	0.0103	0.0116	0.0116	0.0116
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	0.0018	0.0013	-0.0149	-0.0190	-0.0190	-0.0190
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. herf_route		-0.0187	0.0594***	0.0720***	0.0720***	0.0720***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. n_carr			0.0238***	0.0211***	0.0211***	0.0211***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0637***	0.0637***	0.0637***
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.3183***	
					(0.01)	
L. CPIU						-0.0137***
						(0.00)
Constant	4.9163***	4.9273***	4.7424***	4.7127***	5.2394***	7.7308***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
Observations	187312	187312	187312	187312	187312	187312

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A25: H3_BASEMODEL_Sensitivity analysis 125%

	(1) av_freq_incumbents_logged	(2) av_frequ_incumbents_logged	(3) av_frequ_incumbents_logged	(4) av_frequ_incumbents_logged	(5) av_frequ_incumbents_logged	(6) av_frequ_incumbents_logged
L.av_frequ_incumbents_logged	0.0068	0.0071	0.0145*	0.0159*	0.0159*	0.0159*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L. entry_large	-0.0176	-0.0181	-0.0330	-0.0389	-0.0389	-0.0389
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
L. herf_route		-0.0212	0.0614***	0.0736***	0.0736***	0.0736***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L. n_carr			0.0252***	0.0226***	0.0226***	0.0226***
			(0.00)	(0.00)	(0.00)	(0.00)
L. lcc_on_route				0.0625***	0.0625***	0.0625***
				(0.01)	(0.01)	(0.01)
L. fuel_price_logged					-0.3185***	
					(0.01)	
L. CPIU						-0.0137***
						(0.00)
Constant	4.8914***	4.8784***	4.7039***	4.7013***	5.2023***	7.7104***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.09)
Observations	189362	189362	189362	189362	189362	189362

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: H26_BASEMODEL_Sensitivity analysis 175%