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Breaking Down Break Points:

An Analysis of the Effects of Competition and Carrier Type on Ticket Prices.

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Abstract

This research focuses on the effects of competition and carrier type on the point of transition, separating ticket prices in two main periods; one of relatively stable- and predominantly small increases in prices and one where ticket prices start to sharply increase. This research will be applied to the U.S. airline industry, where prices for identical tickets are highly changeable over time. In this research two hypotheses are tested, estimating the effect of competition and carrier type on the point of transition between the two main periods in ticket pricing. Panel data is collected, following prices of tickets for a total of 2,339 U.S. domestic flights on the 100 busiest U.S. domestic routes. A pooled Ordinary Least Squares regression is used to estimate both effects. Effects are found for competition, finding support for advance-purchase discounts theory as the point of transition between the periods occurs earlier under increasing competition. No effects are determined for type of carrier.

The views stated in this thesis are those of the author and not necessarily those of Erasmus School of Economics or Erasmus University Rotterdam.

Contents

I. Introduction

The deregulation of the U.S. airline industry in 1978 is considered to be the main driver of increased competition among airlines, leading to a significant decrease in airfares (Morrison & Winston, 1990). When adjusted for inflation, the average price of a domestic airfare has decreased by almost 50% since 1978 (United States Department of Transportation, 2019). This increased pressure on prices called for more advanced revenue management in order to maintain airlines' profits (Bitran & Caldentey, 2003), in an industry with typically thin margins (International Air Transport Association, 2013).

Over the past years, not only competition increased, ultimately leading to lower prices, but also the total air passenger transport has increased and will continue to increase even further. U.S. domestic air passenger transport has increased with over 50% over the last 15 years (United States Department of Transportation, 2019) and the total air passenger transport is expected to double within the next two decades (International Air Transport Association, 2018).

As Robert Crandall, former CEO of American Airlines, once said: "*If I have 2,000 customers on a given route and 400 different prices, I am obviously 1,600 prices short*". As every consumer has a different willingness to pay, this statement reflects the importance of yield management, as airlines would ideally have as many price points as possible, tapping into all individuals' maximum willingness to pay. These differences in willingness to pay are primarily driven by differences in customer dynamics, allowing airlines to charge different prices to different customers, depending on the time of booking (McAfee & Te Velde, 2006). Dynamic pricing strategies play a large role in yield management, first widely adopted in the airline industry, allowing airlines to change their prices, maximising their revenues. (Smith, Leimkuhler, & Darrow, 1992).

The importance of revenue management is undisputed. Not only the increased competition, the increasing pressure on prices and the increase in total air passenger transport underline this, but also previous research by Smith, Leimkuhler and Darrow (1992), Wittman and Belobaba (2018), Kumar, Li and Wei (2018) and many others find significant benefits for airlines in adopting revenue management systems.

The topic of revenue management goes further than merely economic impact. According to the global academic publisher Palgrave Macmillan "*Revenue management, also known as yield management, marries the diverse disciplines of operations research/management science, analytics, economics, human resource management, software development, marketing, e-commerce, consumer behaviour and consulting*" (Palgrave Macmillan, 2019). This broad set of disciplines demonstrates

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how revenue management interlinks different fields of research. By studying this topic, not only an economic contribution can be made, but research may also contribute to different academic fields of research, vastly expanding the total body of scientific knowledge on revenue management.

The aim of this research is to further investigate market-specific determinants affecting increases in airfares over time under changing prices. The ultimate goal of this research is to determine what the effects of competition and carrier type are, with respect to the point at which the period of relatively stable- and predominantly small increases in prices transitions into the period in which prices start to sharply increase. This will help further understand the effects that competition and firm type have on prices that change over time.

To answer this question, panel data on the 100 busiest U.S. domestic air routes will be used, following prices of 2,339 U.S domestic flights for a period of 103 consecutive days. Consequently, after imposing four restrictions, the point in terms of days prior to departure at which the period of relatively stable- and predominantly small increases in prices transitions into the period in which ticket prices start to sharply increase is determined. Through these restrictions, the point of transition between the two periods is determined for 2,129 out of 2,339 flights.

The effects of competition and carrier type are estimated through a pooled Ordinary Least Squares regression model, finding an effect for competition, indicating that the point of transition between the two periods occurs earlier with increasing competition. No effect is found for carrier type.

Apart from being the first research paper to examine the effect of competition and carrier type on the transition point between the period of relatively stable- and predominantly small increases in prices and the period in which prices start to sharply increase in the airline industry, the novelty of this research paper extends further. Where other research papers follow airline ticket prices for irregular intervals or smaller time periods, this research paper is the first to follow airline ticket prices for an extensive period of 103 days. Moreover, this research paper examines prices for both legacy and low-cost carriers on the 100 busiest U.S. domestic air routes, where other papers focus solely on either legacy or low cost carriers and on fewer routes. Moreover, prior research extensively focusses on monopolistic routes, where this research will focus on competitive routes.

The results found in this research indicate that for more competitive routes, prices start to rise earlier than for less competitive routes. This indicates, that consumers flying on more competitive routes do well to book their flights longer in advance than consumer flying on less competitive routes, to be assured of paying a relatively low fare. Moreover, it indicates that out of the three economic theories that will be examined, the advance-purchase discount theory is most applicable to the airline industry, under ticket prices that change over time.

Moreover, no evidence is found that tickets increase sharply in prices earlier for either low-cost carriers or legacy carriers. Lastly, this research paves the way for a more detailed examination of carrier type, as a difference is found for regional airlines compared to non-regional airlines.

Section two will describe theory and previous research on the topics of revenue management, dynamic pricing, pricing, and industrial organisation. These topics will, through reasoning and previous research, lead towards the research question at the centre of this research, and the proposed hypotheses to answer this research question. Section three will describe the data used to answer this research question, focusing on the sources and its content. Section four will describe the methodology for the empirical analyses that will be done to test the proposed hypotheses. The results of these analyses will be discussed in section five, answering the hypotheses. Section six will answer research question central to this research and discuss the implications of the findings. Finally, section seven will discuss the limitations to this research as a result of data sources and collection, used methodology and validity of results, concluding with recommendation for future research on the topic.

II. Theoretical Framework

Many academics have previously studied the field of pricing, often examining the airline industry, as pricing data on the U.S. airline industry has been made more widely available following the Airline Deregulation Act of 1978 (Gerardi & Shapiro, 2009). As a result, over time extensive bodies of research have accumulated on pricing in general and on pricing in the airline industry. In this research, both will be combined. Moreover, this research will focus on revenue management, more specifically on its aspect of changeable prices over time for an identical ticket.

i) Revenue management

One of the terms of the Airline Deregulation Act of 1978, was that controls of the Federal Government of the United States over fares in the airline industry were removed. As a result, airlines' focus moved away from selling the maximum number of seats available to maximising overall revenue, through revenue management practices (Wang & Bowie, 2009). As revenue management is utilised across different industries, there is no commonly agreed upon definition. Definitions for revenue management are found to vary according to different service sector perspectives (Sieburgh, 1988), (Orkin, 1989), (Lieberman, 1993), (Kimes & Wirtz, 2002).

Although literature has not agreed upon a common definition, consensus is found in that revenue management is a business practice, effective in maximising revenue for fixed or so-called perishable assets, as aeroplane seats or hotel rooms. Moreover, the core concept found back in most definitions is maximising revenue by effectively managing three mechanisms, namely pricing strategy, inventory control and control of availability (Wang & Bowie, 2009). Pricing strategies consist of charging different prices to different customers. Inventory control encompasses the process of allocating seats among various fare classes on a flight leg, and depends on the availability- and use of resources as aircraft, human resources, kerosene, etc. (Wang & Bowie, 2009), whereas control of availability refers to which reservations are accepted and rejected, based on the availability of the pre-determined fare classes on that flight leg (Williamson, 1992).

Throughout the existing literature, the terminologies revenue management and yield management are used interchangeably. Revenue management was first widely adopted in the airline industry (Smith, Leimkuhler, & Darrow, 1992). After its proven success, the concept of revenue management was welcomed to the hotel industry, which has also proven to be a success (Sieburgh, 1988), and later expanded to the wider hospitality- and services sector. Over time, numerous studies have shown a positive effect of revenue management on firm's revenue and profitability; Smith, Leimkuhler and Darrow (1992) estimate that American Airlines' revenue management system contributes to over $500 million incremental revenue on yearly basis. Researches by Kimes (1997) and Cross (1997) find that employing revenue management practices can enhance a firm's revenues with 3-7% without significant capital expenditures and can increase profits in some cases of up to 50-

100%. Donaghy, McMahon and McDowell (1995) expect the increase in profits to be even higher in the airline industry, due to the tighter margins, but do not empirically investigate this. These findings show that the economic importance of revenue management for firms is undisputed.

ii) Dynamic pricing in the airline industry

Under revenue management, three mechanisms are effectively managed, as mentioned above. One of these mechanisms is pricing strategies. Over recent years, the term "dynamic pricing" has increasingly been used in literature on revenue management and airline pricing. With recent technological advancements, new distribution capabilities emerged, allowing airlines to adjust their fares more frequently. This development is seen as the start of the era of dynamic pricing (Wittman & Belobaba, 2019).

As the concept of dynamic pricing is relatively new, the definition of dynamic pricing has been fluid over the last years. In earlier descriptions, dynamic pricing was seen as pricing strategies to increase profits (McAfee & Te Velde, 2006). Other descriptions equate dynamic pricing with revenue management (Escobari, 2012). Dynamic pricing definitions later became more specifically defined as "*a dynamic calculation of the optimal price, taking into account the airline's strategy, customer-specific information, and real-time alternative offerings*" (Fiig, Goyons, Adelving, & Smith, 2016), or defined as "*varying pricing over a continuous interval instead of opening and closing fare classes*" (Kumar, Li, & Wang, 2018).

Although dynamic pricing has increased in popularity over the recent years, Wittman and Belobaba (2019) had to conclude that there had not yet been established a clear-cut definition for this phrase, leaving them to attempt in creating a definitional framework for dynamic pricing mechanisms in their 2019 paper. They propose a definition for dynamic pricing, originating from their 2018 paper, which will also be followed in this research; "*Firms practice dynamic pricing when they charge different customers different prices for the same products, as a function of an observable state of nature*" (Wittman & Belobaba, 2018). Under dynamic pricing, prices for the same product may change over time, which is not possible for static pricing, where prices for the same product remain constant. Here, 'observable state of nature' refers to all information that is available to a firm at the time of pricing, which includes remaining inventory, time remaining in selling window, future demand forecasts, characteristics of the product, determinants in the shopping requests and price of competitor offerings (Wittman & Belobaba, 2019).

Airlines may alter prices for their product as a result of changes in this observable state of nature. Under dynamic pricing, it is possible to change prices as frequently as per completed transaction. In their definitional framework, Wittman and Belobaba (2019) mention and describe the three mechanisms for firms to engage in dynamic pricing, namely assortment optimisation, dynamic price adjustment and continuous pricing. Under assortment optimisation, firms select several prices to offer from a finite set of pre-determined price points, or sub-classes. Airlines define these sub-classes through restrictions as refundability, minimum stay, over-weekend stay, purchasing in advance and many others (Mok, 2019). These sub-classes segment customers through their restrictions, making airlines able to charge different prices for the same product. Under dynamic price adjustment firms select a pre-determined price point, as under assortment optimisation, but then either increase or decrease this price based on restrictions that are revealed from the transaction information. The last mechanism firms can use for dynamic pricing is continuous pricing, where a price is selected from a continuous range of prices, determined by restrictions, optimisation models, remaining inventory, demand, transactional information etc. (Wittman & Belobaba, 2019). These three mechanisms are schematically represented in Appendix A. Assortment optimisation is the most commonly used mechanism for dynamic pricing in the airline industry, as distribution standards were designed to accommodate for this type of dynamic pricing, where dynamic price adjustment and continuous pricing are currently infeasible in the airline industry due to indirect distribution channels (Wittman & Belobaba, 2019). Wittman & Belobaba (2019) also emphasise that dynamic pricing does not mean that prices always change on transactional basis, which is further exemplified through the method of assortment optimisation.

Empirical research is somewhat lacking behind on dynamic pricing in the airline industry, compared to empirical research on ‘regular’ airfares. The Bureau of Transport Statistics of the U.S. Department of Transportation collects and publishes quarterly- and monthly data through their Origin and Destination Survey (DB1B) database and T-100 Domestic Segment (T-100) databank, respectively – on prices, routes, carriers, capacity and other itinerary details. Academics make extensive use of these sources of data. However, databases on dynamic pricing or changes of prices on the same routes over time, are less widely available, making empirical examination of dynamic pricing less occurrent.

McAfee and Te Velde (2006) collect data on prices of four city-pairs for fifteen different take-off dates and find that dynamic pricing is only effective when the probability of selling out significantly changes, approximately in the last 20 tickets on a flight. They find that airlines aim for a positive probability of empty seats, as pricing to sell out is efficient. This finding is consistent with Kumar, Li and Wang (2016), who also find dynamic pricing to be most efficient when the load factor reaches 80-90%. Lazarev (2013) examines the intertemporal effect of dynamic pricing on consumer welfare and distinguishes between the effects for business travellers and leisure travellers. Lazarev (2013) uses manually-collected data on prices up to six weeks prior to flight departures. He finds that (1) prices increase in discrete jumps, (2) the times where the lowest price for flights increase typically occur at 20, 13 and 6 days prior to departure, and (3) prices remain relatively stable in periods between these increases in prices. These findings are attributed to the assortment optimisation as described earlier and differences in elasticity of demand between business and leisure travellers. However, his research only examines monopolistic markets, meaning competitive behaviour is not taken into account. Lastly, Alderighi, Nicolini and Piga (2015) examine the combined effect of remaining capacity and time to departure on fares, for low-cost airline Ryanair by focusing on the highest fares available. They combine capacity-based theory, which states that fares increase when capacity decreases, following supply and demand (Dana, 1999a) with time-based theory, which states that airlines may use intertemporal price discrimination in exploiting customers' differences in willingness to pay and uncertainty (Dana, 1999b), (Gale & Holmes, 1992). They find that fares increase when fewer seats remain available. Moreover, their evidence suggests that less competition on routes makes airlines able to charge higher prices to customers with an inelastic demand, which are typically the late bookers of tickets, than on routes with a higher degree of competition (Alderighi, Nicolini, & Piga, 2015).

iii) Market structures

Over time a large body of knowledge has been established on pricing. This section will focus on previous literature on pricing with regards to industrial organisation. This will specifically examine the aspects of competition – as number of competitors and measures for firm concentration – and type of carrier – legacy or low-cost carrier – as these aspects will hold a central position with respect to the hypotheses posed later in this framework, leading towards answering the research question which will also be discussed further on in this framework.

iii.a) Competition

Morrison and Winston (1990) find that fares fall when competition increases. This finding is consistent with the common economic theory of supply and demand, and with economic pricing theory that states that under Betrand price competition, prices will reach an equilibrium at marginal costs. However, prices are found to depend on the number of competitors, as evidence finds that prices do not equal the predicted Bertrand-competition equilibrium of marginal costs under two competitors, but merely go down to marginal costs after three or four competitors operate in the same market (Dufwenberg & Gneezy, 2000).

Economic theory also predicts that market power increases a firm's ability to price-discriminate, indicating that more competition in a market leads to lower price dispersion. Evidence is however mixed on this topic. Borenstein and Rose (1994) find a positive relationship between competition and price dispersion, which is supported by Carbonneau, McAfee, Mialon and Mialon (2004), whereas Gerardi and Shapiro (2009) find this relationship to be negative. Moreover, Dai, Liu and Serfes (2014) find greater price dispersion in concentrated markets but less price dispersion in competitive markets.

Other reasoning suggests moving away from a homogeneous product to avoid price competition and moving towards product differentiation in terms of performance or service in order to compete on quality rather than prices (Mazzeo, 2003).

iii.b) Advance-purchase discounts

Under advance-purchase discounts some consumers purchase a good at an early date, whilst other consumers purchase the good at a later date, against different prices. This is based on uncertainty about consumers' expected valuation of a good if the consumption takes place in the future (Nocke, Peitz, & Rosar, 2011). Under dynamic pricing it is clear that prices change, generally following an increasing price path over time as a result of decreasing capacity over time and customer segments with different elasticities. As a result of this increasing price path, consumers face a trade-off between buying a good at an early time against the lower, discounted, price or delaying their buying decision to a later point where their true valuation is more clear.

Gale and Holmes (1992) find that airlines with a monopoly on a route do not offer advance-purchase discounts, whereas perfect competition on a route leads to airlines competing over the consumers with elastic demand through offering advance-purchase discounts. This is consistent with later findings by Dana (1998).

iii.c) Carrier type

Consequently, within a market's structure, competition can further differ. The airline industry knows two main types of firms, namely low-cost carriers and (national) legacy carriers, or network carriers. Each type follows different business models. On the one hand, low-cost carriers operate point-to-point, charge lower fares, operate the same or largely similar aircraft type, which they use intensively, minimising idling time. On the other hand, legacy carriers operate a hub-and-spoke network, charge higher fares, offer full service flights including meals and drinks, and offer extensive loyalty programmes and customer service (KPMG, 2013). Both models target a different customer base. Low-cost carriers typically aim for leisure travellers whereas legacy carriers typically aim at the business travellers' segment (Dresner, 2006).

Research by Dresner, Lin and Windle (1996) finds that if a low-cost carrier enters on a route, this leads to lower prices of and a higher passenger volume. Prices dropped by around 38% if a low-cost carrier entered the route. The found effect seemed to be the largest if low-cost carrier Southwest Airlines entered the route, due to its low costs and aggressive pricing strategy. Furthermore, Brueckner, Lee and Singer (2013) have found in-market competition from legacy carriers to have a limited effect on fares, whereas competition from low-cost carriers will highly reduce fares.

iv) Pricing phases over time

As a result of dynamic pricing, prices of airline tickets differ over time, following a certain pattern. This can be related to stock pricing, as identical stocks may also differ over time in prices. In general, stocks also follow a certain pricing pattern. Wyckoff (1931) defined four different stages in stock pricing, namely the accumulation phase, run-up phase, distribution phase and run-down phase.

The first phase is the accumulation phase. In this phase investors slowly start acquiring a stock against an attractive, low, price. This is also called the basing period, in which a minimal amount of stock is sold. Through the so-called support- and resistance levels a price range is defined in which investors buy. In the accumulation phase the price range is often small. The second phase is the run-up phase, indicating the stock prices continue to increase in an uptrend, as more investors start buying. The third phase is the distribution phase, in which earlier traders from the accumulation phase and the run-up phase exit and sell their stocks. This phase is characterised by high volumes, and a stagnation of prices. The final phase is the run-down phase, in which the strongly reduced demand and increased selling by investors drives down stock prices (Investopedia, 2018).

The phases of stock pricing are separated by a transition point, the so-called break-outs or break points (Nicholas, 2008). A schematic illustration of the four phases can be found in Appendix B.

These phases will be related to prices of tickets in the airline industry in the following paragraphs.

iv.a) Accumulation phase applied to airline pricing

The accumulation phase can be seen as the first phase of ticket prices. The first tickets that come available are the cheapest as they offer airlines the certainty that flights will attract enough passengers (KLM, 2019). Here ticket prices follow a similar distribution as in the accumulation phase, as attracting enough passengers can be seen as establishing the base load. An advance-purchase discount method is used to establish a base load. Under advance-purchase discounts in the airline industry, discounts are given to consumers booking up to 30 days prior to departure (Gale & Holmes, 1992). Gale and Holmes (1992) state that through offering advance-purchase discounts, airlines evenly allocate customers with low time costs, or 'indifferent' customers, over their flights, which allows airlines to concentrate on the consumers with high time costs, or stronger preferences, which are typically the business travellers which buy their tickets closer to departure date. This is consistent with later findings by Dana (1998).

Academic research on the first phase is scarce. McAfee and Te Velde (2006) find prices to fluctuate initially. This is underlined by empirical research conducted by Etzioni, Tuchinda, Knoblock and Yates (2003), who compare price data with the lowest prices on a flight with a predictive search algorithm. They find that in the initial phase, consumers on average overspend on their airline tickets by 27.1%. This indicates, that price-fluctuations of on average 27.1% in the first phase of pricing are not uncommon in the airline industry. When examining the data used in this research, fluctuations seem to appear in the accumulation phase, consistent with findings by McAfee and Te Velde (2006).

iv.b) Run-up phase applied to airline pricing

The run-up phase marks the end of the accumulation phase, as prices go up. More extensive academic research has been conducted on the run-up phase, in which prices of airline tickets are found to increase. The main consensus is that ticket prices are found to increase due to the combined effect of decreasing remaining capacity and decreasing time till departure (Alderighi, Nicolini, & Piga, 2015). Prices are found to vary as a result of differences is willingness to pay, caused by differences in customer dynamics (McAfee & Te Velde, 2006). These differences in customer dynamics are exploited through restrictions in tickets, leading to different prices, as explained through the assortment optimisation methods.

iv.c) Distribution phase and run-down phase applied to airline pricing

As it is not (yet) possible to resell airline tickets, the distribution phase and the run-down phase are discarded, as theory by Wyckoff (1931) states that the distribution and run-down are largely affected by resale of stocks.

Evidence by Möller and Watanabe (2010) suggests ticket price to go down as departure nears, mimicking a clearance sale or so-called last-minute tickets as tickets are so-called perishable goods, consistent with the final phase of run-down. However, anecdotal evidence of Dutch legacy carrier KLM states that prices go up exponentially in the last few days prior to departure, as their target for this period is the business traveller with an inelastic demand function (Mok, 2019). This difference in academic evidence and anecdotal practical evidence yields inconclusive views on the behaviour of airline tickets in the last days before a flight departs, theoretically making the existence of the fourth phase of run-down still possible.

However, the phase of run-down seems unlikely, as the extent of perishability varies between different goods. Anjos, Cheng and Currie (2005) distinguish between two types of perishable goods, namely manufactured goods and service goods. Manufactured goods have a limited shelf-life, such as food or clothing. After this shelf-life, the products still have value, as clothing can still be worn when it is considered out of fashion, or food can be processed or used to feed animals. The salvation value of the product is positive. Service goods, such as flight seats or hotel rooms, also have a limited shelf-life, as a flight cannot be sold after its departure and a hotel room cannot be sold for a passed date. In contrast to manufactured goods, for service goods the salvation value past this life is zero, as an unsold product is worthless past this date (Gallego & Van Ryzin, 1994). Li (2001) argues that airline seats are perishable, non-storable (or service) goods, and that if firms offer multiple prices, these prices will always be increasing over time, as consumers will otherwise expect decreases in prices and accordingly postpone their purchase. This is seen as the main reason for not offering clearance sales or last-minute tickets in the airline industry.

Moreover, when taking a first glance at the data used in this research paper, which will be explained in more detail later in this research in section three, data, the run-down phase seems non-existent in this dataset leaving us to focus solely on the accumulation phase and the run-up phase.

iv.d) Break points

The above-discussed phases can be separated by break points, as defined by Nicholas (2008). Values for change points are determined in different ways, depending on the academic field studied, making not one value or percentage universally agreed upon. In finance literature, Kim and Kon (1999) define change points as extreme values at which stock returns exceed a 4.5% threshold. In the medical field Worsley (1988) finds significant change points at 5% thresholds when examining relapses in leukaemia. For the airline industry 4.5% - 5% seems as a too conservative estimate, as price differences between fare sub-classes seem larger (Mok, 2019). Nicholas (2008) measures excess returns at 32% when examining stock returns by using citations to proxy innovation. Furthermore, Li, Xu, Zhong and Li (2019) examine brain activity under normal weight and overweight conditions and examine a change point at 30%.

These differences in break points across research fields, complicate choosing an appropriate break point for this research. Moreover, to our knowledge break points have not been applied to the airline industry, as to date. How break points will be defined in this research paper will be explained in more detail in section four, methodology.

Section 3, data, will provide first insights in the data used in this research paper. It will also show the distribution of ticket prices over time, illustrating the phases in relation to ticket prices, the break points and the support- and resistance levels.

v) Hypotheses development

Previously, the phases of stock pricing have to our knowledge not yet been related to industrial organisation. Moreover, these phases have neither been related to airline tickets before. In the airline industry research focussed on the run-up phase, where ticket prices increase significantly, has been plentiful. However, the accumulation phase for airline tickets, where the ticket prices remain within a certain price range, has been underexposed in scientific research. This research paper will focus on how the break point between the first phase – the accumulation phase – and the second phase – the run-up phase is affected by competition and carrier type in the airline industry. This research will further examine the aspects of competition, in terms of number of carriers and concentration of carriers, as well as the type of carrier operating on given routes. The research question examined in this research is:

"How do competition and carrier type affect the break point between the accumulation phase and run-up phase of airline tickets under dynamic pricing in the airline industry?"

This research question will be tested through two hypotheses. The first hypothesis will look at the effect of competition on the break point between the accumulation phase and the run-up phase. Several economic views arise on the effect of competition, which can be applied to the break point.

v.a) Bertrand competition

Morrison and Winston (1990) find that an increase in competition in a market, decreases fares. Bertrand pricing theory states that prices will reach an equilibrium at marginal costs. Dufwenberg and Gneezy (2000) find that this only occurs after three or four competitors are operating in the same market. Under common economic pricing theory, more competition is expected to lead to lower prices. As more competitors in a market leads to a larger total supply, it is expected to take longer to fill the base load in the accumulation phase, moving the break point closer towards the departure date.

v.b) Advance-purchase discounts

Furthermore, research on advance-purchase discounts by Gale and Holmes (1992) suggests that under perfect competition, airlines offer advance-purchase discounts, as opposed to monopolists who do not offer advance-purchase discounts. As competition grows stronger, the advance-purchase discounts become larger. Thus it can be reasoned, that a break point may occur further away from a flight's departure date under increasing competition.

v.c) Product differentiation

Moreover, Mazzeo (2003) finds competition leads to more product differentiation as competitors compete on quality rather than prices. As carriers no longer compete on prices under this view, the effect of competition on the break point is expected to be non-existent.

Above-mentioned researches leave for undecided views on this topic. This research paper will consider all three mentioned theories, with eventually in section five, results, finding either a positive effect, a negative effect or no effect. Consequently, it will be determined whether Bertrand competition, advance-purchase discount or the product differentiation view, respectively, best describes the effect of competition on the break point.

Here, competition will be measured through three different ways, namely through the Herfindahl-Hirschman Index as most common measure for competition, the Number of carriers on a route and the Market share of a carrier on a route. Above reasoning leads to the following, first, hypothesis:

Hypothesis 1: *"More competition will cause the break point between the accumulation phase and run-up phase to differ."*

The second hypothesis will look at the effect of the type of carrier. In the airline industry two carrier types are predominant, namely legacy carriers and low-cost carriers. These two types follow different business models, targeting different customer segments. Under static prices it is known that low-cost carriers offer uniformly lower fares than legacy carriers. However, under dynamic pricing considerations, the difference between legacy carriers and low-cost carrier has been underexposed. As prices differ under static pricing, prices are also expected to differ under dynamic pricing. Above reasoning leads to the second hypothesis:

Hypothesis 2: *"The break point between the accumulation phase and run-up phase differs between low-cost carriers and legacy carriers."*

III. Data

To test the hypotheses introduced in section two, and consequently answer the research question central to this research paper, a panel dataset on cheapest ticket fares of flights will be used.

i) Main body of the data

The main body of the data is manually collected for the purpose of scientific research. The 100 busiest U.S. domestic routes in terms of total passengers transported in the year 2017 have been selected. For all flights on these routes departing on October 22, 2018, the lowest available fares have been tracked daily, starting 103 days prior to departure of the flight, starting on July 11, 2018. This data has been obtained through scraping data off ITA Matrix, the base Google Flights, and the website of Southwest Airlines[1]. The dataset contains 239,304 observations, observing 2,339 flights on the 100 busiest U.S. domestic routes, as multiple carriers operate on the same route and often even operate multiple flights on the same day. This means the panel is unbalanced. Each observation contains itinerary details as the origin, destination, flight number, days to departure, operating carrier, duration, price, class, sub-class, aircraft, and by which carrier the flight is operated if a code-sharing agreement is in place. Furthermore, in this dataset each flight is seen as a series, resulting in a maximum of 103 observations per series, one for each day the flight is tracked. The 100 busiest U.S. domestic routes that will be examined in this research paper can be found in Appendix C. As it is unsurprisingly that the 100 busiest U.S. domestic routes are all 'competitive' routes, on which at least two airlines operate, this characteristic of the dataset allows focus on pricing under competition. This characteristic allows for Bertrand competition, leading towards the first hypothesis, as argued in section two, theoretical framework. Even though 77% of all U.S. domestic routes are monopolies (Airline Network News and Analysis, 2013), the routes selected in this sample are the 100 busiest U.S. domestic routes, which are estimated to account for approximately 70-80% of total U.S. passenger transport (United States Department of Transportation, 2019). The prices in the dataset are equal to the price consumers ultimately pay for the flight, meaning additional charges as luggage handling fees and security fees, etc. are included. All prices are single-direction fares.

The dataset contains ten airlines, namely Alaska Airlines, American Airlines, Delta Air Lines, Frontier Airlines, Hawaiian Airlines, JetBlue, Mokulele Airlines, Southwest Airlines, Spirit Airlines and United Airlines. Of these airlines Frontier Airlines, JetBlue, Southwest Airlines and Spirit Airlines are considered low-cost carriers (Vowles & Lück, 2016). Through the most common definition of legacy carriers, in which an airline has established interstate routes before the Airline Deregulation Act of 1978 (Vowles & Lück, 2016), only Alaska Airlines, American Airlines, Delta Air Lines and United

[1] As Southwest Airlines solely publishes its fares on its own website, fares for flights operated by Southwest Airlines were not available through ITA Matrix. As Southwest Airlines is ranked first in domestic passengers carried (International Air Transport Association, 2015), it was chosen to include Southwest Airlines in the dataset examined in this research paper through obtaining its fares from its own website.

Airlines would be considered as legacy carriers. However, in this research we will also view Hawaiian Airlines and Mokulele Airlines as legacy carriers, solely based on the fact that they are not low-cost carriers, which is the main distinction used in the second hypothesis.

ii) Construction of the final sample

ii.a) Merging data

In addition, other variables are added to the dataset, mainly as independent variables or to control for confounding effects, relevant for section four, methodology.

First of all, a binary choice variable will be created to distinguish low-cost carriers from non-low-cost carriers as described earlier. Furthermore, a binary choice variable will be created to distinguish ultra-low-cost carriers. Lastly, a binary choice variable will distinguish regional carriers. These further distinctions are made to examine not only differences between legacy carriers and low-cost carriers, but consequently further examine the differences between carrier-type, when ultra-low-cost carriers and regional carriers are also included. As defined by Bachwich and Wittman (2017), ultra-low-cost carriers in this dataset are Spirit Airlines and Frontier Airlines. Regional airlines in this dataset are Hawaiian Airlines and Mokulele Airlines, as these solely operate on routes on Hawaii (Mokulele Airlines) or on Hawaii and to mainland United States (Hawaiian Airlines) in this dataset.

Secondly, for all routes the total non-stop distance is added as control variable, as distance is a major factor affecting the level of prices charged (United States Department of Transportation, 2019). The non-stop distance is obtained through the Department of Transportation's Domestic Airline Fares Consumer Report. This report examines the 1,000 largest U.S domestic city-pair markets quarterly, since 1996. As the airline industry and its routes have evolved over the years, not all routes selected in this research are among the 1,000 largest in 1996. The distances of the remaining routes are obtained through distance-cities.com, after validating both methods use the same approximation, by comparing the known distances. Prior research on prices in the airline industry extensively uses distance as control when examining prices.

Thirdly, the dataset contains information on the type of aircraft operated on each flight. Through each airline's fleet details, obtained through their website, it is possible to determine the seating capacity for passengers on each of their flights. Through this seating capacity, supply can be proxied. Each airline flies a different configuration of aircraft, even though the type may be the same. As of this, the capacity of the same type of aircraft may vary amongst airlines. Capacity data is collected on all aircraft types operated by the ten carriers examined in this research paper. However, not only do the aircraft configurations between carriers differ, it is also possible that a carrier operates aircraft of the same type with different seating configurations. As it is not possible to precisely determine which seating configuration a carrier flies on the given flights, and thus the corresponding capacity of a carrier on a given flight is unclear, the capacity for the flights on which carriers operate multiple seating configuration for the same type of aircraft, is proxied by taking the most occurring configuration that the carrier operates of the said types[2].

Fourthly, additional data on the routes is added to control for further route-specific effects. Data on population of Metropolitan Statistical Areas for 2018 is obtained through the U.S. Census database. Moreover, the income per capita for each Metropolitan Statistical Area was obtained through the U.S Census database. For obtaining the income per capita by Metropolitan Statistical Area, data as of March 2018 is used, as this is the most recent data available. Income per capita is measured in U.S dollars. The average monthly load factor for domestic routes for U.S. carriers is determined for October 2018 through the Bureau of Transportation Statistics' T-100 Domestic Segment databank, alongside with the yearly average load factor for domestic routes by U.S. carriers over 2018. All observations for monthly- and yearly load factors, are time-invariant as they are industry averages.

Fifthly, data on carrier specific characteristics is added. The average load factor per carrier is also obtained through the T-100 databank. As data for Mokulele Airlines was not available, it will be proxied by the average load factor for destination Kahului, as city pair Honolulu – Kahului is the only route Mokulele Airlines operates on in the collected sample. Available seat miles are also obtained through the T-100 databank and calculated for Mokulele Airlines[3]. Available seat miles are measured in thousands. Total domestic passengers per carrier is also added, as a control for size, also obtained through the T-100 databank. Domestic net income over 2018 is also obtained through the T-100 databank, measured in thousands of US dollars. Furthermore, data on operating revenue, operating expense, total assets in the fourth quarter of 2018 and total cash is obtained through the Bureau of Transportation Statistics' Air Carrier Financial Reports (Form 41 Financial Data), collected from schedules B-1 and P1.2, all measured in thousands of US dollars.

The additional variables are merged into the main body of the data. The proxy for distance is perfectly merged, as it was possible to determine the non-stop distance of all routes. The proxy for passenger capacity is not perfectly merged, as the main body of the data contains several missing values for the variable aircraft type, on which the passenger capacity is merged, as a result of data collection issues, further touched upon later in this section. The available seat miles per carrier are perfectly merged, along with the monthly load factor of October 2018 per carrier as well as the yearly load factor for 2018 per carrier, as all flights depart in October 2018. Total passengers transported, net

[2] E.g.in 2018, American Airlines operated four different configurations of the Airbus A321-200, ranging in seating capacity between 102 and 190 passengers. As most aircraft in service were configured for seating 190 passengers, this number is taken as a proxy for capacity.

[3] As data on Mokulele Airlines is not available through the T-100 databank, either due to their size, as a result of being acquired by Southern Airways Express in 2019, or not reaching the $20 million dollar requirement to be included in the database, the available seat miles for Mokulele is calculated by multiplying their 787 weekly flights (Globe Newswire, 2019) with their aircraft capacity of 9 passengers with the average distance of their routes, which is 101 miles.

income, assets, operating expenses, operating revenues and cash have missing values for Mokulele, as explained in footnote 3.

ii.a) Transformations in data

Furthermore, several variables are transformed. "Distance^2" is added, as distance is found to have a non-linear effect on prices – it takes fuel to carry fuel – and is extensively used in prior literature. It is now also possible to determine the available seat miles for each flight, by multiplying the distance with the passenger capacity. Furthermore, it is also possible to determine the market share of carriers, as well as the number of carriers on a route and the Herfindahl-Hirschman Index (HHI), which are all common (control) variables used in existing literature. Market share of carriers is determined by dividing the number of flights per carrier on a given route by the total number of flights on these routes, where a higher market share indicates a larger proportion of flights is operated by the carrier. Number of carriers on a route is determined by the total number of carriers that operate on a given route, where a higher value indicates more carriers are active on a route and routes are more competitive. HHI of a route is determined by taking the sum of all squared market shares of carriers operating on the given route, where an HHI of 1 indicates a monopoly, and a low HHI indicates firms competing in the same market. Accordingly, several variables will be transformed into natural logarithms, to facilitate interpretation. The variables 'total available seat miles', 'total passengers transported', 'net income', 'total assets in 2018 Q4', 'operating expenses', 'operating revenues', and 'cash' will be transformed into logarithms. Furthermore, the itinerary details regarding the time of departure are transformed into 3 binary choice variables, namely 'morning flight', 'afternoon flight' and 'evening flight', assuming value 1 if flights are morning- afternoon- or evening flights, respectively. By doing this, it is possible to control for preferred flight times and differing competitive conduct over the day. Morning flights are classified as flights leaving between 05:00 AM and 11:59 AM. Afternoon flights are classified as flights leaving between 12:00 PM and 17:59 PM. Evening flights are classified as flights leaving between 18:00 PM and 05:00 AM.

ii.b) Descriptive statistics

Descriptive statistics of the most meaningful variables can be found in Appendix D. The variable 'Countdown' denotes the days prior to departure of a flight. The dataset contains 239,304 observations for countdown, as data is gathered on each day before departure. Data is collected from 103 days prior to departure up until the day before departure for 2,339 flights. The mean of -52.057 does not equal -52, indicating not all days are observed. Further examination reveals that data is not collected for all days prior to countdown for each flight (Appendix E), indicating it some flights in this sample sold out before departure. The trend shown in Appendix E appears not strictly decreasing, indicating at some point tickets for a once sold-out flight were again made available. This may be caused through either cancellation of tickets by consumers or rescheduling a larger aircraft on this flight by the carrier. The dataset contains 123 missing values for prices of tickets[4]. The prices of tickets in this sample are measured in USD and range between $25 and $1,980. The cheapest tickets of $25 are tickets from Atlanta – Orlando and Salt Lake City – Denver. The most expensive ticket in this sample of $1,980 is a ticket from Chicago – Washington, observed two days prior to departure. The average price of a ticket in this sample is $156.94. The number of carriers on a route ranges from two to six, with an average of 3.83. A binary choice variable denotes whether a carrier is considered to be a low-cost carrier (1) or not (0), as defined by Vowles and Lück (2016). The average value of 0.22 indicates that for most of the observations in this sample the carrier does not classify as a low-cost carrier, as only 22 percent of the observations in the dataset observe a low-cost carrier. A second binary choice variable denotes whether a carrier is considered to be an ultra-low-cost carrier (1) or not (0), as defined by Bachwich and Wittman (2017). The average value of 0.06 indicates that for most of the observations in this sample the carrier does not classify as an ultra-low-cost carrier, as only six percent of the observations in the dataset observe an ultra-low-cost carrier. A last binary choice variable denotes whether a carrier is considered to be a regional airline (1) or not (0). The average value of .03 indicates that for most of the observations in this sample the carrier does not classify as a regional airline, as only three percent of the observations in the dataset observe a regional airline. The passenger capacity of aircraft operated on flights in this sample ranges between 9 and 288, with an average of 157. Aircraft with a capacity of 9 passengers are Cessna (Light), operated on city pair Honolulu – Kahului by island-hopper Mokulele Airlines. Aircraft with a capacity of 288 passengers are Boeing 777, operated on Atlanta – Los Angeles and Los Angeles – Atlanta by Delta Air Lines. Lastly, the distance of routes in this sample range between 101 and 2,619 miles. The shortest route in this sample, at 101 miles, is the route between city pair Honolulu and Kahului, operated by Mokulele Airlines in Cessna (Light) and Hawaiian Airlines in Boeing 717. The longest route in this sample, at 2619 miles, is the route between New York (JFK) and San Francisco, operated by Alaska Airlines, American Airlines, Delta Air Lines and JetBlue. The population of Metropolitan Statistical Areas ranges from 167,295 for Kahului – Wailuku – Lahaina and 19,979,477 for New York – Newark – Jersey City. Furthermore, the income per capita ranges between $41,480 for the Orlando – Kissimmee – Sanford Metropolitan Statistical Area and $91,459 for the San Francisco – Oakland – Hayward Metropolitan Statistical Area. Further descriptive statistics on the control variables are also found in Appendix D.

Moreover, the dataset contains data on 2,339 flights. These flights can be categorised by type of carrier, as specified earlier in this section. Of these 2,339 flights, 516 flights are operated by low-cost carriers as distinguished by Vowles and Luck (2016), 137 flights are operated by ultra-low cost

[4] These missing observations are caused by changes in flight schedules, e.g. change of departure time. As a result of changes in the itinerary details, it was not possible to match the scraped data to the correct corresponding flight, for 123 observations. This is negligible, as this is only a small proportion of the 239,304 total observations.

carriers as distinguished by Bachwich and Wittman (2017) and are also included in the low-cost carriers, and 70 flights are operated by regional airlines.

Finally, Appendix F graphically shows a typical pattern of the development of prices over time, for an Alaska Airlines flight, operated on Anchorage – Seattle. The figure graphically illustrates the accumulation phase and run-up phase by Wyckoff (1931), as described in section two, theoretical framework, when applied to dynamic pricing in the airline industry. The figure also shows the break point, which appears to be located around 21 days prior to departure.

ii.c) Differences with regard to prior research

The final dataset used is expected to give more insight in the effect of competition and carrier type than prior research by exploiting several differences in data.

Firstly, this research follows ticket prices for an extensive period of 103 consecutive days. Prior research on dynamic pricing follows ticket prices for a shorter or more irregular period. Lazarev (2013) follows ticket prices for merely six weeks. Alderighi, Nicolini and Piga (2015) follow prices at thirteen dates in time, namely at 1, 4, 7, 10, 14, 21, 28, 35, 42, 49, 56, 63 and 70 days prior to departure. McAfee and Te Velde (2006) follow prices for flights departing on different dates, thus examining different time horizons per flight, gathering prices around 87 days prior to departure.

Secondly, this research examines the 100 busiest U.S domestic routes, in terms of total passengers transported in 2017, thus examining multiple carriers, multiple routes and multiple flights per route. Prior research by McAfee and Te Velde (2006) examines four city pairs.

Moreover, as this research examines the 100 busiest U.S. domestic routes, with 2 or more carriers operating on all of these routes, this research will examine the differences in competition and carrier type. This is opposed to prior research by Alderighi, Nicolini and Piga (2015), who focus solely on European low-cost carrier Ryanair, and research by Lazarev (2013), who focusses solely on monopolistic routes.

IV. Methodology

This section will determine the methodology to test the hypotheses posed in section two, theoretical framework, and consequently answer the research question "*How do competition and carrier type affect the break point between the accumulation phase and run-up phase of airline tickets under dynamic pricing in the airline industry*". This section will first discuss how break points will be determined in this research paper. Thereafter, the identification strategy will be discussed, which will be used to answer the hypotheses through a pooled Ordinary Least Squares regression model.

i) Specifying breakpoints:

Visually, it is easy for humans to determine the break point between the accumulation phase and the run-up phase. However, when modelling this with this large amount of data, criteria are needed to determine whether a break point is present or not. This poses a number of difficulties. These difficulties arise through strictly increasing prices, one-day-spikes due to selling out, and decreases in prices as a result of assortment optimisation in fare classes, and will be countered through several restrictions as will be discussed below.

The most obvious criterion would be the point where a constant, non-increasing phase of prices changes into an increasing phase of prices. However, this poses the first challenges, as for most flights, prices are found to be strictly increasing, meaning there is no constant phase and a break point can never be determined. This calls for a restriction regarding increases in prices.

Moreover, as airlines use assortment optimisation techniques, it is possible that fare classes sell out, leaving only the more expensive business class tickets available, with prices decreasing back to the lower level the next day when a next fare class opens. This selling-out of fare classes results in a one-day-spike before prices return to the lower levels, which would be seen as a break point.

Furthermore, Wittman and Belobaba (2019) emphasise that under dynamic pricing, prices do not have to vary on transactional basis, as a result of assortment optimisation. This poses for another characteristic which should be taken into account. As long as fare classes are still opened, prices need not vary the next day, meaning prices need not be strictly increasing after a break point. To counter these problems, the first restriction would be that prices need to be increasing or constant – or not decreasing – for a break point to occur.

Moreover, to establish a base load in the accumulation phase, cheaper fare classes are frequently opened or closed through assortment optimisation. To counter the fluctuation of prices due to assortment optimisation, a total of 7 days is taken, in which prices are not allowed to decrease, in order to determine a break point. This further sharpens the first restriction to "no decrease in prices for at least 7 days in order for a break point to occur".

Furthermore, in establishing a base load in the accumulation phase, cheaper fare classes are frequently opened or closed through assortment optimisation, resulting in prices fluctuating over the accumulation phase. However, as these changes are typically relatively small, a restriction needs to be imposed for the change of prices to distinguish between the accumulation phase and the run-up phase. Kim and Kon (1999) measure excessive returns in stocks by a 4.5% threshold on a daily basis. Combined with the earlier restriction of 7 days, this gives a cumulative increase of 31.5%, which will be maintained as threshold for break points in this research. The value of 31.5% reflects values used in prior research investigating differences between periods, as Nicholas (2008) uses 32% and Xu, Zhong and Li (2019) take 30%, as mentioned in section two, theoretical framework.

Consequently, to correctly determine the break point, a restriction is put into place to ensure that the break point is determined at the day that prices start to increase, requiring prices to increase the following day. This restriction aims to mitigate the effect of large increases, due to opening of more expensive fare classes, and excludes the days that prices remain constant.

Lastly, to ensure that prices keep increasing, and percentage changes are not solely attributed to a one-off increase of prices as a result of the opening of merely one more expensive fare class, a further restriction requires a second opening of a more expensive fare class within the 7-day-window, mentioned earlier. This ensures that prices keep increasing and a one-off opening of a more expensive fare class earlier in the accumulation phase is not considered as a break point, whilst taking into account the critical note of Wittman and Belobaba (2019) stating prices need not be increasing on a transactional basis.

To sum up, a break point between the accumulation phase and the run-up phase exists when all following conditions apply:

i) Prices are not decreasing for at least 7 days,

and

ii) A cumulative increase in prices of more than 31.5 percent over the following 7 days occurs,

and

iii) Prices increase next day,

and

iv) Prices increase at least twice over the following 7 days.[5]

[5] Having to acknowledge that the number of days and value for percentage increase in prices are chosen somewhat arbitrarily, sensitivity analyses will determine whether the signs of the effect of competition and carrier type on the break point change under different thresholds.

Concludingly, as further restrictions aimed to eliminate break points in the earlier period of pricing would strongly reduce the number of observations of break points in the phase closer to departure, observed break points up to 35 days prior to departure date are disregarded when determining the final break points. This is done following research by Alderighi, Nicolini and Piga (2015), who categorise bookings up to 35 days prior to departure as 'early-booking-days'.

For each flight, a break point will be determined at the number of days prior to departure, for which the above-mentioned restrictions first apply. As the dataset used for this research contains 100 routes, with a total of 2,339 flights, a maximum of 2,339 break points will be determined. If said restrictions do not apply to a flight, no break point will be determined for this flight and this flight will not be further examined in the regression model.

The table and figure shown in Appendix G give further insight in how the break points are determined, by examining a flight on the route Los Angeles – San Francisco, operated by Alaska Airlines. The final column of table 3 indicates if earlier-mentioned conditions i) – iv) are all met, which is the case at 64, 61, 22 and 16 days prior to departure. As 64 and 61 days prior to departure are considered as 'early-booking-days' following Alderighi, Nicolini and Piga (2015), these are not considered as break points, thus 22 days prior to departure is considered as the first occurrence of a break point for this particular flight.

After the breakpoints are determined for each flight, the panel is collapsed to form one observation per flight, allowing us to examine the effect of included variables on the break point between the accumulation phase and run-up phase.

The found break points will be examined through an independent samples t-test, to determine whether the means of the break points for the legacy carriers and low-cost carriers are statistically different from each other. Consequently, the means for ultra-low-cost carriers and regional airlines will be examined through an independent samples t-test.

ii) Identification strategy and regression model

To test the hypotheses, a pooled Ordinary Least Squares regression model will be used. The regression model follows the following identification strategy:

$$\text{Break Point}_{ijt} = \beta_0 + \beta_1\,\text{HHI}_j + \beta_2\,(\text{HHI}_j \times \text{Low-Cost Carrier}) + \beta_3\,\text{Low-Cost Carrier}_{ijt} + \gamma_1\,X + \varepsilon_{ijt}$$

In the above-mentioned equation, indexes i denote carrier, indexes j denote route and indexes t denote flights. The dependent variable 'Break Point' denotes the days prior to departure at which the break point between the accumulation phase and run-up phase occurs, taking value 1 the day prior to departure, and 103 at 103 days prior to departure. β_0 denotes the intercept, or constant term. 'HHI' is an independent variable which denotes the measure for competition. This is measured as the Herfindahl-Hirschman Index, an index used to determine market competitiveness, increasing when markets become less competitive, with β_1 denoting its corresponding coefficient. 'HHI × Low-Cost Carrier' is an independent variable which denotes the interaction effect of HHI for low-cost carriers, with β_2 denoting its corresponding coefficient. 'Low-Cost Carrier' is a binary choice variable, assuming value 1 if a carrier is a low-cost carrier and value 0 if the carrier is not considered a low-cost carrier, with β_3 denoting its corresponding coefficient.

In the equation, X is a vector of control variables, with γ_1 denoting its corresponding coefficient. The control variables included in the vector X are listed in Table 1, below.

Table 1 Control variables included in vector X, with specified type of effect

Control variable	**Type of effect**
Average Monthly Load Factor	Industry effect
Average Yearly Load Factor	Industry effect
Monthly Load Factor	Carrier-specific
Yearly Load Factor	Carrier-specific
Ln(Total Available Seat Miles)	Carrier-specific
Ln(Total Passengers Transported)	Carrier-specific
Ln(Net Income)	Carrier-specific
Ln(Total Assets)	Carrier-specific
Ln(Population in Origin City)	Route-specific
Ln(Income in Origin City)	Route-specific
Distance	Route-specific
$Distance^2$	Route-specific
Afternoon Flight	Flight-specific
Evening Flight	Flight-specific
Aircraft Capacity	Carrier-, Route- and Flight-specific

By adding the mentioned control variables, we control for industry, carrier-specific, route-specific, and flight-specific characteristics.

ii.a) Hypothesis 1

To test the first hypothesis ("*More competition will cause the break point between the accumulation phase and run-up phase to differ.*"), the pooled Ordinary Least Squares regression model will be estimated, following the above-mentioned identification strategy.

The coefficient β_1 denoting the estimated effect of the competition will be examined. To find support for the first hypothesis, the estimated coefficient of competition proxied by the HHI on the break point is expected to be statistically significant, as this indicates that an effect is indeed present[6].

Finding a positive effect for competition on the break point, indicates that the break point occurs further away from departure. Consequently, a negative effect of competition on the break point, indicates that the break point occurs closer to departure.

If a negative and significant effect for competition is found, competition moves the break point closer to departure, finding support for common economic theory, expecting lower prices under higher competition and a longer time to fill the required base load in the accumulation phase.

If a positive and significant effect for competition is found, competition moves the break point further from departure, finding support for advance-purchase discount theory, expecting a larger discount for more competitive routes compared to less competitive routes, resulting in a break point occurring later in the booking process, or closer to departure.

If no significant effect is found, competition does not affect the break point, finding support for the product differentiation theory, stating that competition will be on quality and not on prices, as proposed by Mazzeo (2003).

When examining the effect of the HHI on the break point, it is important to take into account how HHI is measured. A higher HHI indicates less competition and a lower value for HHI indicates more competition. If HHI is found to have a positive effect on the break point, the break point occurs further away from departure if competition decreases. If HHI is found to have a negative effect on the break point, the break point occurs closer to departure if competition decreases.

Furthermore, in the above-mentioned identification strategy, the independent variable HHI will be replaced with the number of carriers on a route and market share of carriers on a route as a robustness test, as it is possible to measure competition through different ways. To find support for the first hypothesis, the estimated coefficients are also expected to be statistically significant. As the number of carriers increases under increasing competition, the signs are expected to be mirrored as to the expected signs under HHI. As a higher market share indicates less competition, similar to the HHI, the coefficients are expected to follow the same direction as under HHI.

[6] The dataset contains negative values for days to departure, meaning the observations examined 20 days prior to departure are denoted by a value of -20 for the variable 'Countdown'. As a result, the break points are initially also calculated including these negative values. To facilitate interpretation, these values will be transformed into absolute values. After this transformation, a positive relationship will result in a larger value for the break point, indicating a break point occurs further away from departure. Consequently, a negative relationship will result in a smaller value for the break point, indicating a break point occurs closer to departure.

A 5%-significance level will be maintained for independent variables in this analysis, meaning support is found for the second hypothesis if the found coefficient of β_1 is statistically different from zero at a 5% significance level.

ii.b) Hypothesis 2

To test the second hypothesis ("*The break point between the accumulation phase and run-up phase differs between low-cost carriers and legacy carriers.*") the pooled Ordinary Least Squares regression model will again be estimated following the above-mentioned identification strategy.

The coefficient β_2 denoting the estimated interaction effect of competition and low-cost carriers on the break point, along with the coefficient β_3 denoting the estimated effect of low-cost carriers on the break point will be examined. To find support for the second hypothesis, the estimated coefficient of the interaction effect of competition and low-cost carriers on the breakpoint is expected to be statistically significant. This effect is also expected to be significant for the number of carriers on a route and the market share of carriers on a route.

Moreover, and arguably more important for the analysis leading towards answering the second hypothesis, the estimated coefficient for β_3 is expected to be statistically significant.

Furthermore, the identification strategy will be estimated with the interaction effect and independent binary choice variable for low-cost carriers replaced by the binary choice variables denoting ultra-low-cost carriers and regional airlines, to determine the respective effects.

A 5 percent significance level will be maintained for independent variables in this analysis, meaning support is found for the second hypothesis if the found coefficient for β_3 is statistically different from zero at a 5 percent significance level.

ii.c) Endogeneity in this analysis

Under endogeneity, an independent variable is correlated with the error term, leading to biased and inconsistent estimations, which is caused by omitted variables, measurement errors in independent variables and simultaneity bias (Woolridge, 2009).

By including earlier-mentioned control variables, the so-called omitted variable bias is reduced.

Furthermore, as the data is collected from ITA Matrix and the Southwest Airlines website, measurement errors are unlikely, as these are the true prices paid by consumers.

According to Gerardi and Shapiro (2009) the airline industry is a classic example of simultaneity bias, as entry and exit on routes occurs frequently. It is often debated whether competition affects prices or prices affect competition on a route. It can be argued that low fares lead to high competition, or that high competition can lead to low fares. Moreover, high (low) fares can make a route more (less) attractive, causing carriers to enter (exit) on this route. However, this research paper counters the simultaneity problem by using data collected over 103 days. In the short time span of this sample, no carriers have ceased to operate on any of their routes or entered on any new routes examined in this sample.

Due to reducing the omitted variable bias by including control variables, not expecting measurement errors and not expecting a simultaneity effect due to carriers entering or exiting on routes, endogeneity problems are countered in this research paper.

V. Results

After applying the conditions as specified in section four, methodology, a break point is determined for 2,129 out of 2,339 flights. Appendix H shows the distribution of the determined break points. Eye-catching is the clustering of break points around 14 and 7 days prior to departure. This is in accordance with dates prior to departure at which prices start to sharply increase, as found in earlier research by Lazarev (2013). Finding break points for 2,129 out of 2,339 flights, means 210 flights in the dataset do not contain a break point between the accumulation phase and run-up phase under the earlier specified conditions. The lack of a break point is a result of not all four specified conditions simultaneously applying to a flight for any of the given days prior to departure. Appendix I gives further insight as to why for some flights a break point is not determined, by examining a flight on the route New York (LaGuardia) - Chicago, operated by United Airlines.

i) Preliminary Evidence

Appendix J shows independent samples t-tests for the break points of low-cost carriers, ultra-low-cost carriers and regional airlines. The dataset contains 516 flights operated by low-cost carriers, 137 flights operated by ultra-low-cost carriers and 70 flights operated by regional airlines. Break points are found for 485 of these 516 flights for low-cost carriers, 127 out of 137 flights for ultra-low-cost carriers and 29 out of 70 flights for regional airlines. The mean break point for low-cost carriers is located at 13.480 days prior to departure, compared to 11.620 days prior to departure for its non-low-cost carrier counterparts[7,8]. The found p-value of 0.0000 for the independent samples t-test implies that the mean of the break points determined for low-cost carriers is statistically different from the mean of the break points determined for non-low-cost carriers. Moreover, the mean break point for ultra-low-cost carriers is located at 15.315 days prior to departure, compared to 11.837 days prior to departure for non-ultra-low-cost carriers[9]. The found p-value of 0.0000 for the independent samples t-test again implies that the mean of the break points determined for ultra-low-cost carriers is statistically different from the mean of the break points determined for non-ultra-low-cost carriers. Furthermore, the mean break point for regional airlines is located at 8.448 days prior to departure, compared to 12.094 days prior to departure for non-regional airlines[10]. The found p-value of 0.0047 for the independent samples

[7] It should be noted that the dataset used in this research reports days prior to departure as a negative value. Therefore, the distribution of break points shown in Appendix H also displays negative values. To facilitate interpretation, the break points are transformed into absolute values, when describing the results found through the pooled Ordinary Least Squares regression model, as described in section four, methodology.

[8] The group 'low-cost carriers' include Frontier Airlines, JetBlue, Southwest Airlines and Spirit Airlines, following Vowles & Lück (2016). The group 'non-low-cost carriers' include Alaska Airlines, American Airlines, Delta Air Lines, Hawaiian Airlines, Mokulele Airlines and United Airlines.

[9] The group 'ultra-low-cost carriers' include Spirit Airlines and Frontier Airlines, following Bachwich and Wittman (2017). The group 'non-ultra-low-cost carriers' include Alaska Airlines, American Airlines, Delta Air Lines, Hawaiian Airlines, JetBlue, Mokulele Airlines, Southwest Airlines and United Airlines.

[10] The group 'regional airlines' include Hawaiian Airlines and Mokulele Airlines. The group 'non-regional airlines' include Alaska Airlines, American Airlines, Delta Air Lines, Frontier Airlines, JetBlue, Southwest Airlines, Spirit Airlines and United Airlines.

t-test implies that the mean of the break points determined for regional airlines is statistically different from the mean of the break points determined for non-regional airlines. However, it should be noted that with 29 determined break points for regional airlines, the number of observations for regional airlines is likely not large enough to make meaningful comparisons.

This preliminary evidence indicates that the mean of break points indeed significantly differ among carrier types. Preliminary evidence shows that the means of the break points for ultra-low-cost carriers occur earliest, at 15.315 days prior to departure, followed by low-cost carriers at 13.480 days prior to departure, followed by non-low-cost carriers, or legacy carriers at 11.620 days prior to departure, and the mean of break points for regional carriers occurs latest, at only 8.448 days prior to departure. This indicates, that the differences between legacy carriers and low-cost carriers (and ultra-low-cost carriers) found under static pricing, may also exist under dynamic pricing conditions. A further econometric analysis will be conducted which should point out whether the found difference is caused by carrier type or merely affected through other variables.

ii) Main results

ii.a) Main results hypothesis 1

To test the first hypothesis ("*More competition will cause the break point between the accumulation phase and run-up phase to differ.*"), the pooled Ordinary Least Squares regression model is estimated following the identification strategy as determined in section four, methodology. The results can be found in Table 2 on the next page.

In the pooled Ordinary Least Squares regression, the industry averages of load factors are not included, as a result of perfect collinearity. The coefficients of the remaining variables are estimated.

Table 2 shows a negative coefficient for the competition proxy Herfindahl-Hirschman Index on the break point of -9.444, which is significant at a 1 percent significance level. This indicates that if the Herfindahl-Hirschman Index on a route increases by 0.100, indicating the route becomes less competitive, the break point will occur 0.944 days earlier, ceteris paribus. Thus, competition measured as HHI is found to affect the break point.

Moreover, when examining the robustness test for number of carriers, shown in the second column of Table 2, a positive effect for the number of carriers on a route on the break point of 0.810 is found, which is significant at a 5 percent significance level. This indicates that if the number of carriers on a route increases by 1, indicating the route becomes more competitive, the break point occurs 0.810 days later, ceteris paribus. Thus, competition measured as number of carriers on a route is also found to affect the break point.

Furthermore, when examining the robustness test for market share of carriers on a route, shown in the third column of Table 2, a negative coefficient for the market share of carriers on a route

Table 2 Pooled Ordinary Least Squares regression on Break Point with HHI, number of carriers on route and market share route carrier

VARIABLES	Break point (HHI)	Break point (Number of carriers on route)	Break point (Market share route carrier)
Constant	-15.80	-53.36	-74.30
	(43.65)	(48.32)	(48.28)
HHI_j	-9.444***		
	(2.503)		
Number of carriers on $route_j$		0.810**	
		(0.311)	
Market share of carriers on $route_{ij}$			-4.982***
			(1.439)
Low-cost $carrier_{ijt}$	-1.638	5.176	-3.918
	(5.405)	(5.813)	(6.163)
× HHI_j	14.52***		
	(5.143)		
× Number of carriers on $route_j$		-1.378**	
		(0.576)	
× Market share of carriers on $route_{ij}$			13.67***
			(4.969)
Monthly load $factor_i$	118.3	202.8*	217.4*
	(107.9)	(110.3)	(118.4)
Yearly load $factor_i$	-62.46	-158.6	-136.6
	(126.4)	(126.2)	(136.0)
Ln(Total available seat $miles_i$)	3.320	10.98	11.02
	(8.774)	(9.408)	(9.695)
Ln(Total passengers $transported_i$)	-5.962**	-7.655**	-7.938**
	(2.932)	(3.089)	(3.069)
Ln(Net $Income_i$)	0.883	-0.0823	-0.133
	(1.304)	(1.350)	(1.390)
Ln(Total $Assets_i$)	0.888	-2.566	-2.548
	(4.536)	(4.694)	(4.947)
Ln(Population Origin $City_j$)	-0.459	-0.401	-0.350
	(0.518)	(0.502)	(0.517)
Ln(Income Origin $City_j$)	0.637	1.029	0.796
	(1.328)	(1.287)	(1.317)
$Distance_j$	0.00641***	0.00554***	0.00607***
	(0.00174)	(0.00182)	(0.00185)
$Distance_j^2$	-2.19e-06***	-1.93e-06***	-2.19e-06***
	(5.42e-07)	(5.61e-07)	(5.71e-07)
Afternoon $flight_t$	-0.385	-0.407	-0.410
	(0.332)	(0.331)	(0.334)
Evening $flight_t$	-0.756*	-0.789*	-0.779*
	(0.413)	(0.411)	(0.420)
Aircraft $capacity_{ijt}$	-0.000628	-0.00374	0.00415
	(0.00523)	(0.00521)	(0.00559)
Observations	2,127	2,127	2,127
R-squared	0.071	0.062	0.065

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

on the break point of -4.982 is found, which is significant at a 1 percent significance level. This indicates that if the market share of a carrier on a route increases by 10%, indicating a decrease in competition, the break point will occur 0.498 days earlier, ceteris paribus. Thus, competition measured as market share of a carrier on a route is also found to affect the break point.

The results of the analysis conducted to answer the first hypothesis show a negative, statistically significant effect of the HHI on the break point. This results in a positive effect of competition on the break point, indicating that if competition increases, the break point occurs earlier in the booking process, or further away from departure. Furthermore, when measuring competition through different ways, competition is still found to have a positive, statistically significant effect on the break point.

This indicates support is found for the first hypothesis, establishing there is indeed an effect of competition on the break point between the accumulation phase and the run-up phase. Moreover, the found effect is positive, thus finding support for advance-purchase discount theory in the U.S. airline industry under dynamic pricing.

ii.b) Main results hypothesis 2

To test the second hypothesis ("*The break point between the accumulation phase and run-up phase differs between low-cost carriers and legacy carriers.*") the pooled Ordinary Least Squares regression model is estimated following the identification strategy determined in section four, methodology, which is also used to test the first hypothesis. Thus, the results can again be found in Table 2, on the previous page.

Again, the industry average effects of load factors are not included in the pooled Ordinary Least Squares regression, as a result of perfect collinearity.

Table 2 shows no significant effects for the binary choice variable indicating whether a carrier is considered a low-cost-carrier, on the break points. This indicates that although the means found in the independent samples t-tests discussed in the preliminary evidence paragraph of the results section differ between type of carrier, this relationship is not causal.

When examining the estimated interaction effect of competition for low-cost carriers on the break point, we find a positive effect for the Herfindahl-Hirschman Index, at a 1 percent significance level, a negative effect for the number of carriers on a route, at a 5 percent significance level, and a positive effect for the market share of carriers at a 1 percent significance level. This indicates that a decrease in competition causes the break point to occur further from departure for low cost carriers than for legacy carriers, ceteris paribus.

As the coefficient for the binary choice variable denoting carrier type is found to be insignificant, carrier type is not found to directly affect the break point between the accumulation phase and the run-up phase, therefore rejecting the second hypothesis.

The results for ultra-low-cost carriers and regional airlines can be found in Appendix K and Appendix L, respectively.

When examining ultra-low-cost carriers, the effects for the variables proxying competition are found to be statistically significant, and follow the same signs as found earlier. However, the interaction effects no longer have a statistically significant effect. Moreover, carrier type remains statistically insignificant, indicating carrier type does not affect the break point.

When examining regional airlines, the competition proxy Herfindahl-Hirschman Index is found to have a statistically significant effect on the break point. Moreover, carrier type is found to affect the break point, indicating that the break point occurs closer to departure for regional airlines compared to non-regional airlines, ceteris paribus.

ii.c) Results control variables

Control variables are included in an attempt to reduce confounding effects, which could lead incorrect estimations of the found coefficients of the main independent variables (Stock & Watson, 2015). As a result, control variables are not used to estimate a causal effect. However, it is possible to examine the sign of control variables and consider whether the found signs are in line with theory and/or expectations, which will be attempted in this section for the results found in the main model. The control variables that are found to be significant are 'Monthly load factor', 'Ln(Total passengers transported)', 'Distance', 'Distance^2' and 'Evening flight'.

The effects found for 'Monthly load factor' are positive, but only statistically significant in the models with Number of carriers and Market share of carriers as proxy for competition, at a 10 percent significance level. The findings of the signs are in line with expectations, as an increase in load factor can lead to a change in the break points, as ticket price is largely determined through demand and remaining capacity. Moreover, 'Monthly load factor' could affect the break point through competition, as a higher load factor indicates more demand, ceteris paribus, over which carriers compete. Furthermore, 'Monthly load factor' could affect the break point through carrier type, as low-cost carriers are found to typically have higher aircraft utilisation rates than legacy carriers.

The effects found for 'Ln(Total passengers transported)' are negative and statistically significant for all models, at a 5 percent significance level. The variable is included to control for size of carriers. The found signs are not in line with expectations, as an increase in total passengers transported indicates an increase in demand, ceteris paribus. As a result, flights are expected to fill up faster, reaching the base load built in the accumulation phase earlier in the booking process, consequently bringing forward the break point. Thus, the expected sign would be positive, but the found coefficient is negative. Moreover, the total passengers transported can affect the break point through carrier type, as low cost carriers typically have higher aircraft utilisations rates than legacy carriers.

The effects found for ‘Distance’ and ‘Distance^2’ are positive and negative, respectively, and statistically significant at a 1 percent significance level for all models. This indicates that the effect of distance on the break point is non-linear. The contrasting signs indicate that initially the effect of distance on the break point is positive, however, the effect grows less strong when the distance increases. As the longest distance of the routes observed in this sample is 2619 miles, the effect of distance on the break point never becomes negative. Distance is expected to have a negative effect on the break point, as operating costs are expected to rise with distance, resulting in a ‘larger’ base load involving more customers. Thus, the expected sign would be negative, but the found coefficient is positive. Furthermore, distance can affect the break point through carrier type, as low-cost carriers operate on the typically shorter point-to-point networks, compared to the legacy carriers that can reach longer distances through their hub-and-spoke networks.

Lastly, a negative effect is found for ‘Evening flight’, which is statistically significant at a 10 percent significance level, for all models. Compared to morning flights (the base category), a flight departing in the evening negatively affects the break point. This affect may be attributed to differences in preferences in departure times. However, as preferences vary, no clear expectations were made as of the sign of flights’ departure times.

VI. Conclusion

This research focusses on the effect of competition and carrier type on the break point between the accumulation phase and run-up phase of stock pricing applied to airline tickets. Through examining the effect of competition on the break point, this research will examine three different theories applied to the airline industry under dynamic pricing, namely the common economic pricing theory under Bertrand competition, the advance-purchase discount theory, and the theory of product differentiation. Consequently, the effect of carrier type on the break point is examined.

To answer the research question *"How do competition and carrier type affect the break point between the accumulation phase and run-up phase of airline tickets under dynamic pricing in the airline industry?"*, two hypotheses were tested.

Hypothesis 1: *"More competition will cause the break point between the accumulation phase and run-up phase to differ."*

Hypothesis 2: *"The break point between the accumulation phase and run-up phase differs between low-cost carriers and legacy carriers."*

To test the hypotheses, pricing on 2,339 flights over the 100 busiest U.S. domestic routes is collected, following prices for a consecutive period of 103 days. Additional control variables are added to adjust for confounding effects. After specifying four restrictions, break points between the accumulation phase and run-up phase are determined. Following the four restrictions, break points are determined for 2,129 out of 2,339 flights. Consequently, a pooled Ordinary Least Squares regression is estimated for the break points. Competition is found to have a positive effect on the break point between the accumulation phase and run-up phase, ceteris paribus. As a result, support is found for the advance-purchase discount theory, suggesting the common economic pricing theory under Bertrand competition and the product differentiation theory do not apply to this case. Furthermore, preliminary evidence found a difference in means of break points for different carrier types. Further examinations concludes that the break point is not found to differ between low-cost carriers and legacy carriers as a result of the type of carrier, ceteris paribus. Moreover, further evidence shows that for regional carriers the break point occurs closer to departure than for non-regional carriers.

These finding have both economic and practical implications.

Firstly, as competition on a route increases, the break point between the accumulation phase and the run-up phase occurs earlier. This means customers can face significantly higher prices for their ticket if they postpone their purchase on a more competitive route. Although the main consensus prior to this research was that prices for airline tickets increase over time, this research shows that the period in which ticket prices start to sharply increase, occurs even earlier for more competitive routes, measured as Herfindahl-Hirschman Index, number of carriers and market share of carriers. This finding should urge consumers to book their ticket even earlier in advance if they travel on relatively competitive routes. This is most applicable for leisure travellers, as they book their tickets longer in advance compared to business travellers and have a more elastic demand.

Secondly, as consumers will book their tickets earlier in advance as a result of this research, this calls for more advanced revenue management systems of airlines, as they have to anticipate this increase in ‘early-booking days’. Future research will have to turn out how this in its turn affects the break point, which will be discussed in more detail in the following Limitations and Discussion section.

Thirdly, the break points are not found to differ as a result of carrier type between low-cost carriers and non-low-cost carriers – or legacy carriers, as defined in the theoretical framework. This means that consumers need not book further in advance for either legacy or low-cost carriers in order to buy a cheaper ticket in the accumulation phase, ceteris paribus. However, the model estimating the effect of number of carriers on the break point finds that for regional carriers the break point occurs later, or closer to departure than for non-regional carriers. This implies, that the period in which prices start to sharply increase occurs later for regional carriers, meaning consumers that fly with regional carriers can slightly postpone their purchase and still pay the lower price of tickets charged in the accumulation phase, ceteris paribus.

This research counters the problems of endogeneity as defined by Woolridge (2009). This is done by adding several control variables, to adjust for confounding effects, reducing the omitted variable bias. Furthermore, as data is obtained through ITA Matrix, the Southwest Airlines website and government sources as the Census database and Department of Transportation databases, we deem measurement error unlikely. Moreover, as explained in section four, methodology, we counter the simultaneity problem by using data for the period of 103 days, in which no entrance or exit of carriers on the observed routes occurs. By accounting for this, the estimates are expected to be consistent.

To answer the research question *“How do competition and carrier type affect the break point between the accumulation phase and run-up phase of airline tickets under dynamic pricing in the airline industry?”*, competition is found to have an effect on the break point between the accumulation phase and run-up phase of airline tickets under dynamic pricing. An increase in competition causes the break point to occur further away from the departure date, or earlier in the booking process, ceteris paribus in accordance with advance-purchase discounts theory. No effect for carrier type is found on the break points, when distinguishing between low-cost-carriers and non-low-cost carriers. For regional airlines a break point occurs closer to the departure date than for non-regional carriers, ceteris paribus.

VII. Limitations and Discussion

This section aims to address the limitations of this research and make recommendations for future research.

A first limitation of this research lies in the definition of dynamic pricing used in this research, as determined by Wittman and Belobaba (2018): "*Firms practice dynamic pricing when they charge different customers different prices for the same product, as a function of an observable state of nature*". The 'observable state of nature' refers to all information that is available to a firm at the time of pricing, which includes remaining inventory, time remaining in selling window, future demand forecasts, characteristics of the product, determinants in the shopping requests and price of competitor offerings (Wittman & Belobaba, 2019). Unfortunately, we are not able to control for all these determinants, as not all data is publicly available or attainable. Especially data on remaining inventory is difficult to obtain through public sources. However, as remaining supply strongly affects prices, as capacity is finite, this is also expected to affect the position of the break point. Consequently, further research should take into account the remaining capacity. This can be proxied in the same way as done in Alderighi, Nicolini and Piga (2015). Here, queries were done for the maximum number of tickets per airline. If the airline did not return a valid fare for this request of maximum number of tickets, it could be determined that the remaining tickets were less than this request. By requesting queries of 1 less ticket until the request was accepted, the total number of remaining tickets could be determined. By including the remaining capacity in this way, it is possible to accurately control for remaining inventory, which is one of the factors that determines the price of a ticket (Wittman & Belobaba, 2019). It should be noted that when using this method, the price for 1 ticket is the cheapest fare, with the corresponding remaining capacity being obtained through the maximum number of ticket for which the query is accepted.

A second limitation to this research is that it does not take hub-effects into account, as discussed in Morrison and Winston (1990). An airport may be seen as a hub for particular carriers. Moreover, larger airports or hubs may have a better connectivity to other airports, resulting in a hub-premium included in prices on certain routes, as determined in Borenstein (1989) and Evans and Kessides (1993). This hub-premium in prices is examined by Borenstein (1989) and Evans and Kessides (1993) under static pricing considerations. However, it may differ over time, under dynamic pricing considerations, i.e. increase as the date of departure nears, as this customer segment typically has a more inelastic demand. This hub-dominance may affect competition and number of flights per carriers, in its turn influencing the break point.

A third limitation to this research lies in the types of carriers. The most obvious distinction is made between low-cost-carriers and non-low-cost carriers (or legacy carriers). We further distinguish by ultra-low-cost carriers and regional airlines. However, the proportion of ultra-low-cost carriers and regional airlines is much smaller (137 and 70 observations, respectively). Out of these 137 observations for ultra-low-cost carriers, break points are determined for 127 flights. Out of the 70 observations for regional airlines, break points are determined for a mere 29 flights. This sample may not be large enough to determine meaningful effects, hence this is a possible explanation for the insignificant effects of competition and carrier type for ultra-low-cost carriers and regional airlines. By examining a dataset including more flights operated by ultra-low-cost carriers and regional airlines, it can be determined whether there is indeed no effect as found in this research paper, or this research paper's findings are caused by not examining enough observations.

Fourthly, the effect of alliances, which are highly common in the airline industry, is not taken into account in this research. Brueckner and Whalen (2000) find that alliance partners charge interline fares that are approximately 25% lower than fares charged by carriers that are not in an alliance, under static pricing. Further research should turn out if fares are uniformly 25% lower, or if this differs over time. If the fares are uniformly lower, this will not affect the break point. However, if the fares are found to differ under dynamic pricing considerations, i.e. more in the earlier or later stages of pricing, alliances may affect the break point, and the effect of alliances on the break point should be included in further research on this topic.

Furthermore, Wittman and Belobaba (2019) state that currently continuous pricing is not feasible, but technological advancements may make it feasible in the future. This would dismiss the fare sub-classes, possibly yielding different results than estimated this research, as in our dataset prices largely depend on the sub-classes. Further development of New Distribution Capability standards can lead to a "world without fare classes" according to Westermann (2013). However, this would require significant changes in internal and external airline pricing, revenue management and distribution processes. When continuous pricing becomes increasingly applied to the airline industry, it would be interesting to follow the effects, as due to assortment optimisation, prices now still largely depend on the pre-determined sub-classes.

Moreover, this research does not take discounting into account for the airline tickets. McAfee and Te Velde (2006) raise the question whether discounting should be taken into account when examining airline tickets. As of current knowledge, airline tickets are not discounted in existing literature. However, as airline tickets can be bought almost 1 year in advance (Mok, 2019), it could be argued that discounting should indeed be taken into account in analyses of prices. Further consensus on whether or not to include discounting, needs to be reached. However, it should be noted that the difference between including discounting or neglecting it is most likely negligible, and thus is not expecting to significantly influence the break points.

This research does not distinguish between "business routes" and "leisure routes", although McAfee and Te Velde (2006), and Gerardi and Shapiro (2009) clearly show differences between these types of routes caused by differences in customer dynamics and price dispersion. Different customer segments are found to have different elasticities, thus it is likely that carriers operating on predominantly "leisure routes" are less able to increase their prices, thus shifting the break point, or making the break point non-existent. Further research should focus on determining the effect for different 'types' of routes.

Moreover, as mentioned in section four, methodology, the number of days and percentages used to calculate the break point are chosen somewhat arbitrarily. Through conducting sensitivity analyses, shown in Appendix M, we find that when relaxing one of the assumptions and keeping the other three in place, the sign of competition does not change[11]. More striking, however, is that when excluding condition iii) from the determination of break points, the results do not change compared to the main model. This indicates that the third assumption (*Prices increase next day*) does not further filter down break points. This indicates that prices always increase the next day, under restrictions i), ii) and iv). Although it seems this restriction is unnecessary, as prices always seem to increase following a break point, it can be argued that this restriction perfectly describes one of the characteristics of the break points. Moreover, Appendix N shows that when changing the values chosen for days and increase in prices in restriction i) and ii), the signs also do not change. As a result of these sensitivity analyses, we find even more support for the first hypothesis and consequently the advance-purchase discount theory.

It should also be noted that through the imposed restrictions for a break point to occur, a break point is non-existent for 210 out of the 2,339 routes. Further research could focus on why a break point is not found for these routes. When closer examining the routes on which break point are found to be non-existent under current restrictions, it is found that the majority of these routes originate and or destinate on the state of Hawaii, e.g. Honolulu – Los Angeles, Honolulu – Kahului, Los Angeles – Honolulu and Kahului – Honolulu. Further research could investigate if this can be attributed to the regional airlines operating on these routes or other factors not yet taken into account.

Furthermore, our results suggest that the break points will occur earlier as a result of consumers booking their tickets longer in advance. This would call for airlines to react to this, by adapting their revenue management systems. Further research should investigate how this will affect the break point. Theory suggest through this mechanism an equilibrium of the break point will occur at the earliest point in time, at which the tickets come available. However, this seems unlikely, as demand does not start at its peak level, through uncertainty, business travellers being segmented as inelastic, 'late-bookers', and leisure travellers having more elastic, price-sensitive demands. Further research should investigate if the results of this research will influence the break point in the future.

[11] For simplicity, only the results including HHI as dependent variable for competition are included. When measuring competition through number of carriers and market share the sign were found to remain the same.

Moreover, the distribution of leisure/business travellers on a route may also influence this, as mentioned earlier.

Second-to-last, it should be noted that the results found in this study, may not be applicable to other countries. This study is conducted on the 100 busiest U.S. domestic routes in terms of total passenger transported. Research by Assaf and Josiassen (2011) finds differences in productivity and efficiency between European and U.S. airlines. These differences may attribute to differences in prices, affecting the break points. Moreover, the market share of low-cost carriers in Europe is approximately 50%, compared to approximately 40% in the United States (Official Airline Guide, 2019).

Lastly, the dataset used in this research merely contains routes where two or more carriers are active. We cannot say anything about the effects of carrier type compared to monopoly routes. As the main independent variable of this research is competition, the first hypothesis cannot further be examined for monopoly routes.

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Appendix

Appendix A:

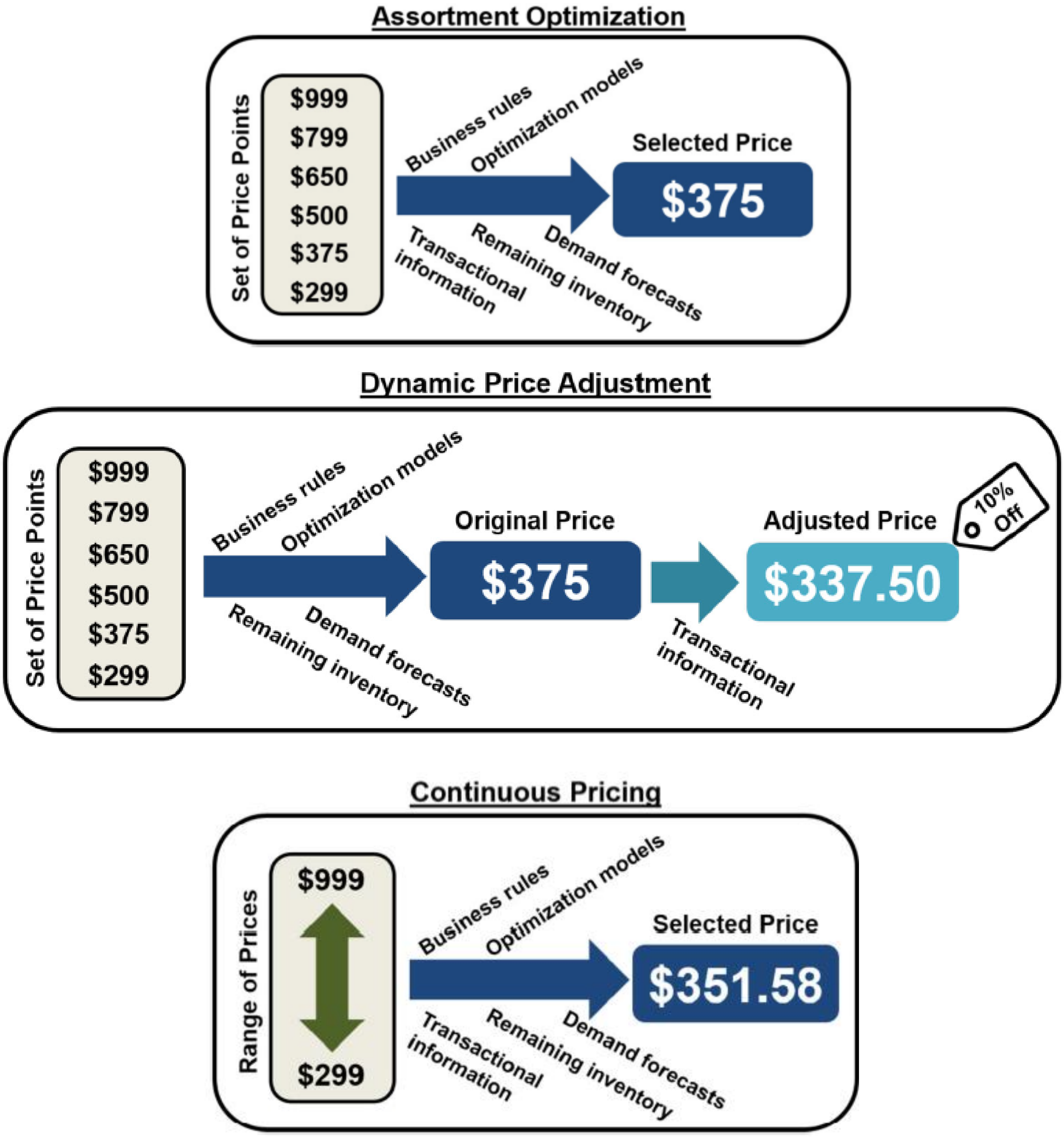

Figure 1 Schematic representation of three mechanisms for firms to engage in dynamic pricing. Source: Wittman & Belobaba (2019).

Appendix B:

Figure 2 Schematic illustration of the four phases in stock pricing. Source: Investopedia (2018).

Appendix C:

Table 3 The 100 U.S. domestic routes selected in this research paper

Route ID	Route		Route ID	Route
1	Anchorage - Seattle		51	Los Angeles - Dallas Fort Worth
2	Atlanta - Boston		52	Los Angeles - Newark
3	Atlanta - Baltimore		53	Los Angeles - Honolulu
4	Atlanta - Washington		54	Los Angeles - New York (JFK)
5	Atlanta - Denver		55	Los Angeles - Las Vegas
6	Atlanta - Dallas Fort Worth		56	Los Angeles - Chicago
7	Atlanta - Detroit		57	Los Angeles - Phoenix
8	Atlanta - Fort Lauderdale		58	Los Angeles - Seattle
9	Atlanta - Los Angeles		59	Los Angeles - San Francisco
10	Atlanta - New York (LaGuardia)		60	New York (LaGuardia) - Atlanta
11	Atlanta - Orlando		61	New York (LaGuardia) - Miami
12	Atlanta - Chicago		62	New York (LaGuardia) - Chicago
13	Atlanta - Philadelphia		63	Orlando - Atlanta
14	Atlanta - Tampa		64	Orlando - Newark
15	Boston - Atlanta		65	Miami - New York (LaGuardia)
16	Boston - Chicago		66	Minneapolis St Paul - Denver
17	Baltimore - Atlanta		67	Minneapolis St Paul - Chicago
18	Washington - Atlanta		68	Kahului - Honolulu
19	Washington - Chicago		69	Chicago - Atlanta
20	Denver - Atlanta		70	Chicago - Boston
21	Denver - Dallas Fort Worth		71	Chicago - Washington
22	Denver - Las Vegas		72	Chicago - Denver
23	Denver - Los Angeles		73	Chicago - Dallas Fort Worth
24	Denver - Minneapolis St Paul		74	Chicago - Los Angeles
25	Denver - Chicago		75	Chicago - New York (LaGuardia)
26	Denver - Phoenix		76	Chicago - Minneapolis St Paul
27	Denver - Seattle		77	Chicago - Phoenix
28	Denver - San Francisco		78	Chicago - San Francisco
29	Denver - Salt Lake City		79	Philadelphia - Atlanta
30	Dallas Fort Worth - Atlanta		80	Phoenix - Denver
31	Dallas Fort Worth - Denver		81	Phoenix - Los Angeles
32	Dallas Fort Worth - Los Angeles		82	Phoenix - Chicago
33	Dallas Fort Worth - Chicago		83	Phoenix - Seattle
34	Detroit - Atlanta		84	San Diego - San Francisco
35	Newark - Fort Lauderdale		85	Seattle - Anchorage
36	Newark - Los Angeles		86	Seattle - Denver
37	Newark - Orlando		87	Seattle - Las Vegas
38	Newark - San Francisco		88	Seattle - Los Angeles
39	Fort Lauderdale - Atlanta		89	Seattle - Phoenix

40	Fort Lauderdale - Newark		90	Seattle - San Francisco
41	Honolulu - Los Angeles		91	San Francisco - Denver
42	Honolulu - Kahului		92	San Francisco - Newark
43	New York (JFK) - Los Angeles		93	San Francisco - New York (JFK)
44	New York (JFK) - San Francisco		94	San Francisco - Las Vegas
45	Las Vegas - Denver		95	San Francisco - Los Angeles
46	Las Vegas - Los Angeles		96	San Francisco - Chicago
47	Las Vegas - Seattle		97	San Francisco - San Diego
48	Las Vegas - San Francisco		98	San Francisco - Seattle
49	Los Angeles - Atlanta		99	Salt Lake City - Denver
50	Los Angeles - Denver		100	Tampa - Atlanta

Appendix D:

Table 4 Descriptive Statistics of the most important variables used in this research paper.

Variable	Obs	Mean	Std.Dev.	Min	Max
Countdown	239,304	-52.057	29.702	-103	-1
Price	239,181	156.944	87.636	25	1980
Number of carriers on route	239,304	3.831	.977	2	6
Low-Cost Carrier (binary choice variable)	239,304	.22	.414	0	1
Ultra-Low-Cost Carrier (binary choice variable)	239,304	.058	.233	0	1
Regional Carrier (binary choice variable)	239,304	.029	.169	0	1
Passenger Capacity	239,181	156.921	38.071	9	288
Distance	239,304	931.873	643.801	101	2619
Population	239,304	7,541,640	5,338,403	167,295	19,979,477
Income Origin (in USD)	239,304	60,967.72	12,684.77	41,480	91,459
Income Destination (in USD)	239,304	60,943.48	12,660.39	41,480	91,459
Ln (Total Available Seat Miles per Carrier in thousands)	239,304	18.45157	.751	10.524	18.853
Ln (Total Passengers Transported per Carrier)	238,480	18.248	.669	16.148	18.885
Ln (Net Domestic Income in thousands of USD)	238,480	13.874	1.020	10.366	14.692
Ln (Total Assets in 2018 Q4 in thousands of USD)	238,480	7.346	.886	14.221	18.077
Ln (Total Operating Expenses in 2018 in thousands of USD)	238,480	16.950	.877	14.526	17.549
Ln (Total Operating Revenue in 2018 in thousands of USD)	238,480	17.053	.875	14.584	17.612
Ln (Domestic Operating Revenue in 2018 in thousands of USD)	238,480	16.760	.776	14.530	17.269
Ln (Cash Available in thousands of USD)	238,480	14.707	1.190	12.391	16.075

Appendix E:

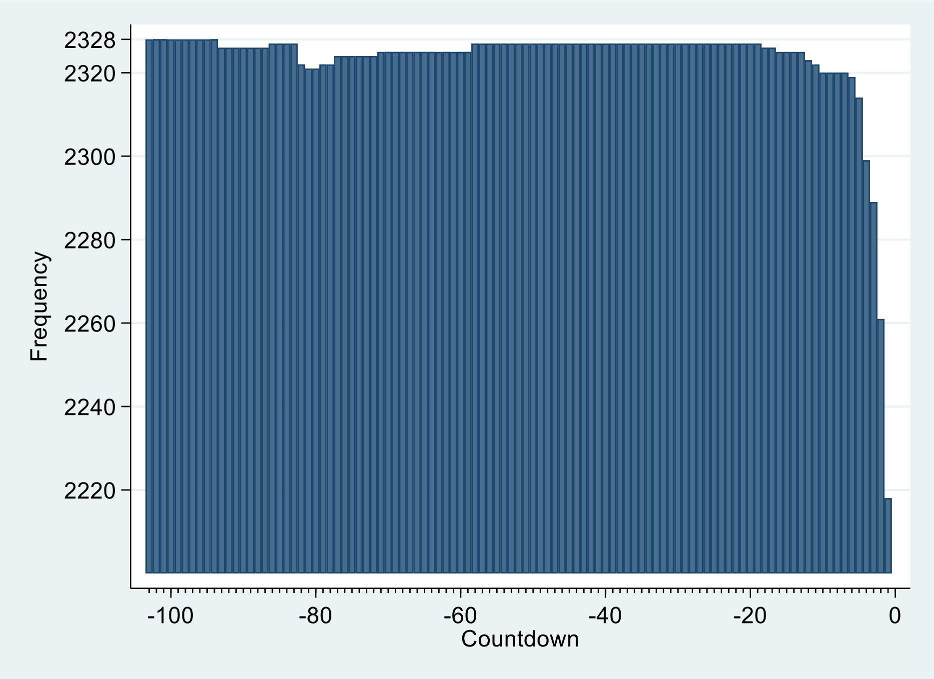

Figure 3 Frequency distribution of observations by Countdown days to departure. The maximum number of observations is 2,328, whereas the lowest number of observations is 2,218, observed 1 day prior to departure.

Appendix F:

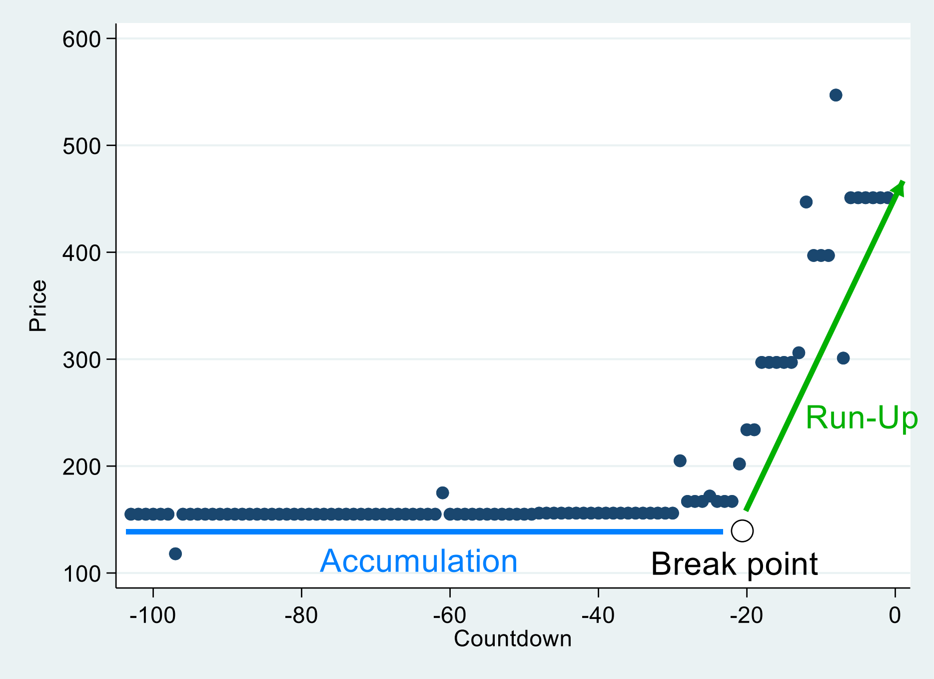

Figure 4 Visual representation of stock phases as described in section two, theoretical framework, applied to a flight on route Anchorage – Seattle, operated by Alaska Airlines. The support- and resistance levels appear to be $118 and $175, respectively. The break point is visually estimated to occur around 21 days prior to departure.

Appendix G:

Table 5 An example of how a break point is determined for a flight on route Los Angeles - San Francisco, operated by Alaska Airlines. A break point is determined if criteria i) – iv) are met. Break points found through this methodology occurring before 35 days prior to departure are disregarded, resulting in the 64th and 61st day prior to departure not being considered a break point and observing the 22nd day prior to departure as the break point for this flight. Percentage change is shown in decimals, and rounded to three decimals. For simplicity, identical observations are clustered to reduce the length of the table.

Count-down to departure date	Price USD	Price Change USD	Percentage Change	(i) No decrease in prices next 7 days	(ii) Cumulative price increase more than 31,5% in following 7 days	(iii) Increase in prices next day	(iv) Increase in prices at least twice over the following 7 days	Break point
-103 → -82	62	-	-	Yes	No	No	No	No
-81	62	0	0	Yes	No	Yes	Yes	No
-80	65	3	0,048	Yes	No	No	No	No
-79	65	0	0	Yes	No	No	No	No
-78	65	0	0	No	No	No	No	No
-77	65	0	0	No	No	Yes	Yes	No
-76	69	4	0,062	No	No	No	No	No
-75	69	0	0	No	No	No	No	No
-74	69	0	0	No	No	Yes	No	No
-73	77	8	0,116	No	No	No	No	No
-72	77	0	0	No	No	No	No	No
-71	75	-2	-0,026	No	No	No	No	No
-70	75	0	0	No	No	No	No	No
-69	75	0	0	No	No	No	No	No
-68	75	0	0	No	No	No	No	No
-67	61	-14	-0,187	No	No	Yes	Yes	No
-66	65	4	0,066	No	No	No	No	No
-65	61	-4	-0,062	No	Yes	No	No	No
-64	61	0	0	No	Yes	Yes	Yes	Yes
-63	75	14	0,230	No	No	No	No	No
-62	75	0	0	No	No	No	No	No
-61	61	-14	-0,187	Yes	Yes	Yes	Yes	Yes
-60	75	14	0,230	Yes	No	No	No	No
-59	75	0	0	Yes	No	Yes	Yes	No
-58 → -54	86	11	0,147	Yes	No	No	No	No
-53	86	0	0	No	No	Yes	No	No
-52	89	3	0,035	No	No	No	No	No
-51 → -48	89	0	0	No	No	No	No	No
-47	86	-3	-0,034	No	No	No	No	No
-46	86	0	0	No	No	No	No	No

-45	86	0	0	No	No	No	No	No
-44	75	-11	-0,128	No	No	No	No	No
-43	86	11	0,147	No	No	Yes	Yes	No
-42	75	-11	-0,128	Yes	No	No	No	No
-41	86	11	0,147	Yes	No	Yes	No	No
-40 → -34	86	0	0	No	No	No	No	No
-33	71	-15	-0,174	Yes	No	Yes	No	No
-32	86	15	0,211	Yes	No	No	No	No
-31 → -23	86	0	0	Yes	No	No	No	No
-22	86	0	0	Yes	Yes	Yes	Yes	Yes
-21	89	3	0,035	Yes	No	Yes	Yes	No
-20	99	10	0,112	Yes	Yes	No	No	No
-19 → -17	99	0	0	Yes	Yes	No	No	No
-16	99	0	0	Yes	Yes	Yes	Yes	Yes
-15	119	20	0,202	Yes	No	No	No	No
-14	119	0	0	Yes	No	Yes	Yes	No
-13	138	19	0,160	Yes	No	No	No	No
-12	138	0	0	Yes	No	No	No	No
-11	138	0	0	Yes	No	Yes	Yes	No
-10	159	21	0,152	Yes	No	No	No	No
-9	159	0	0	Yes	Yes	No	No	No
-8	159	0	0	No	Yes	No	No	No
-7	159	0	0	No	Yes	Yes	Yes	No
-6	160	1	0,006	No	Yes	No	No	No
-5	160	0	0	No	Yes	No	No	No
-4	160	0	0	No	Yes	No	No	No
-3	160	0	0	No	Yes	Yes	No	No
-2	459	299	1,869	No	No	No	-	-
-1	259	-200	-0,436	-	-	-	-	-

Graph shown on next page.

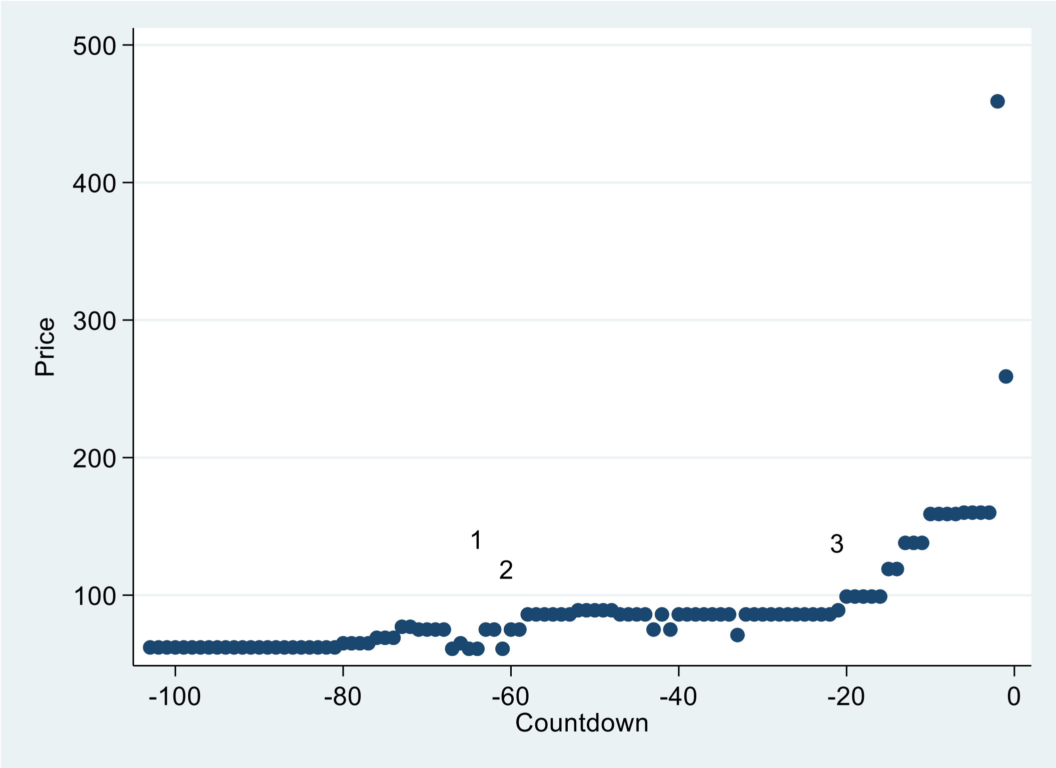

Figure 5 Graph of Price of airline tickets and Countdown for a flight on route Los Angeles - San Francisco, operated by Alaska Airlines. Placemarker 1, 2 and 3 denote the break points found through the methodology explained in section four, methodology. Table 3 shows how the break points are determined in more detail. Break points occurring before 35 days prior to departure are disregarded, as explained in section four, methodology. As a result, the break point for this particular flight is observed at 22 days prior to departure.

Appendix H:

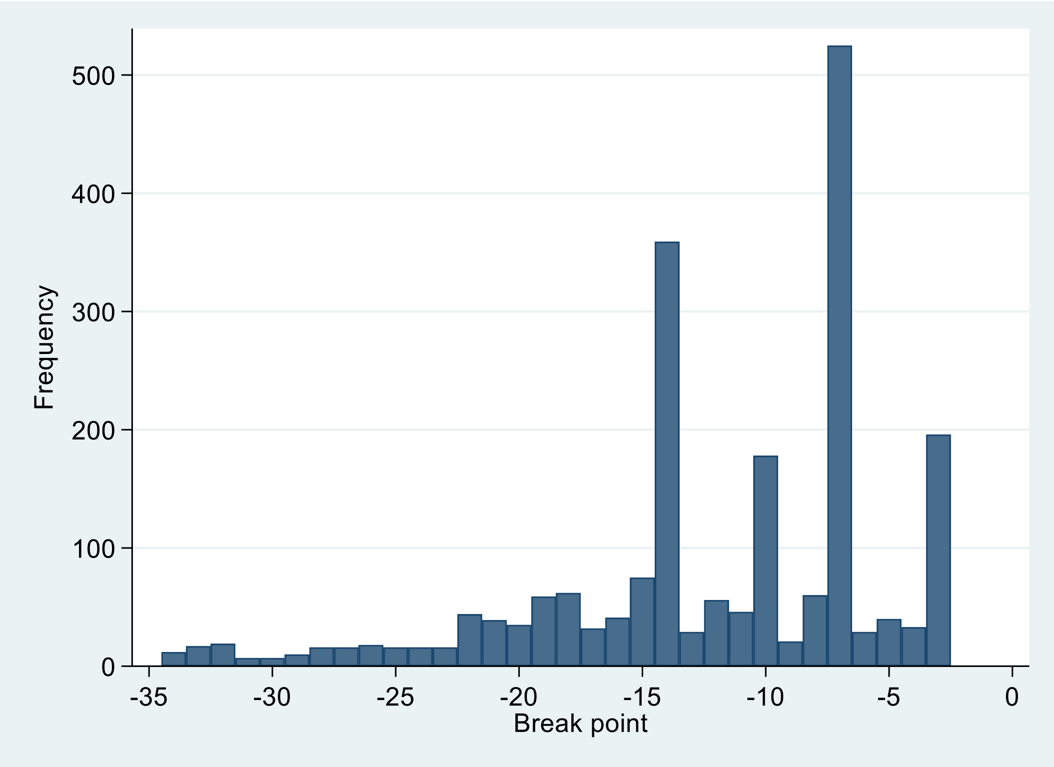

Figure 6 Frequency distribution of found break points for the flights examined in this research paper. 2,129 break points were determined, clustering around 14- and 7 days prior to departure, consistent with earlier findings by Lazarev (2013).

Appendix I:

Table 6 An example of how a break point is attempted to be determined for a flight on route New York (LaGuardia) - Chicago, operated by United Airlines. The last column indicates criteria i) - iv) never all apply. Consequently, no break point is determined for this flight. Percentage change is shown in decimals, and rounded to three decimals.

Count-down to departure date	Price USD	Price Change USD	Percentage Change	(i) No decrease in prices next 7 days	(ii) Cumulative price increase more than 31,5% in following 7 days	(iii) Increase in prices next day	(iv) Increase in prices at least twice over the following 7 days	Break point
-103	128	-	-	No	No	No	No	No
-102	126	-2	-0,016	No	No	No	No	No
-101	126	0	0	No	No	Yes	No	No
-100	166	40	0,317	No	No	No	No	No
-99	166	0	0	No	No	No	No	No
-98	166	0	0	No	No	No	No	No
-97	166	0	0	No	No	No	No	No
-96	126	-40	-0,241	No	No	No	No	No
-95	126	0	0	No	No	No	No	No
-94	96	-30	-0,238	No	No	No	No	No
-93	96	0	0	No	No	No	No	No
-92	96	0	0	No	No	No	No	No
-91	96	0	0	No	No	No	No	No
-90	96	0	0	No	No	Yes	No	No
-89	98	2	0,021	No	No	No	No	No
-88	98	0	0	No	No	No	No	No
-87	96	-2	-0,020	Yes	No	No	No	No
-86	96	0	0	Yes	No	No	No	No
-85	96	0	0	Yes	No	No	No	No
-84	96	0	0	Yes	No	No	No	No
-83	96	0	0	Yes	No	No	No	No
-82	96	0	0	Yes	No	Yes	No	No
-81	126	30	0,313	Yes	No	No	No	No
-80	126	0	0	Yes	No	No	No	No
-79	126	0	0	No	No	No	No	No
-78	126	0	0	No	No	No	No	No
-77	126	0	0	No	No	No	No	No
-76	126	0	0	No	No	No	No	No
-75	126	0	0	No	No	No	No	No
-74	126	0	0	No	No	No	No	No
-73	126	0	0	No	No	No	No	No
-72	96	-30	-0,238	No	No	No	No	No
-71	96	0	0	No	No	No	No	No
-70	96	0	0	No	No	No	No	No

-69	96	0	0	No	No	Yes	No	No
-68	98	2	0,021	No	No	No	No	No
-67	98	0	0	No	No	No	No	No
-66	96	-2	-0,020	Yes	No	No	No	No
-65	96	0	0	Yes	No	No	No	No
-64	96	0	0	Yes	No	No	No	No
-63	96	0	0	Yes	No	No	No	No
-62	96	0	0	Yes	No	No	No	No
-61	96	0	0	Yes	No	No	No	No
-60	96	0	0	Yes	No	No	No	No
-59	96	0	0	Yes	No	No	No	No
-58	96	0	0	Yes	No	No	No	No
-57	96	0	0	Yes	No	No	No	No
-56	96	0	0	Yes	No	No	No	No
-55	96	0	0	Yes	No	No	No	No
-54	96	0	0	Yes	No	No	No	No
-53	96	0	0	Yes	No	No	No	No
-52	96	0	0	No	No	No	No	No
-51	96	0	0	No	Yes	No	Yes	No
-50	96	0	0	No	Yes	No	Yes	No
-49	96	0	0	No	No	No	Yes	No
-48	96	0	0	No	Yes	Yes	Yes	No
-47	126	30	0,313	No	No	No	Yes	No
-46	126	0	0	No	No	No	Yes	No
-45	96	-30	-0,238	No	No	Yes	Yes	No
-44	126	30	0,313	No	No	No	No	No
-43	126	0	0	No	No	No	Yes	No
-42	96	-30	-0,238	No	Yes	Yes	Yes	No
-41	126	30	0,313	No	No	No	No	No
-40	126	0	0	No	No	No	No	No
-39	96	-30	-0,238	No	No	No	No	No
-38	96	0	0	No	No	No	No	No
-37	96	0	0	No	No	Yes	No	No
-36	126	30	0,313	No	No	No	No	No
-35	126	0	0	No	No	No	No	No
-34	126	0	0	No	No	No	No	No
-33	126	0	0	Yes	No	No	No	No
-32	124	-2	-0,016	No	No	No	No	No
-31	124	0	0	No	No	No	No	No
-30	96	-28	-0,226	No	No	No	No	No
-29	96	0	0	No	No	No	No	No
-28	96	0	0	No	No	No	No	No
-27	96	0	0	No	Yes	No	Yes	No
-26	96	0	0	No	Yes	Yes	Yes	No
-25	126	30	0,313	No	No	No	No	No

-24	96	-30	-0,238	Yes	No	No	No	No
-23	96	0	0	Yes	No	No	No	No
-22	96	0	0	Yes	No	No	No	No
-21	96	0	0	Yes	No	Yes	No	No
-20	126	30	0,313	Yes	No	No	No	No
-19	126	0	0	Yes	No	No	No	No
-18	126	0	0	Yes	No	No	No	No
-17	126	0	0	Yes	No	No	No	No
-16	126	0	0	Yes	No	No	No	No
-15	126	0	0	Yes	No	No	No	No
-14	126	0	0	Yes	No	No	No	No
-13	126	0	0	Yes	Yes	No	Yes	No
-12	126	0	0	Yes	Yes	No	Yes	No
-11	126	0	0	Yes	Yes	No	Yes	No
-10	126	0	0	No	Yes	Yes	Yes	No
-9	127	1	0,008	No	Yes	No	Yes	No
-8	127	0	0	No	Yes	No	Yes	No
-7	127	0	0	No	Yes	Yes	Yes	No
-6	283	156	1,228	No	No	No	No	No
-5	283	0	0	No	No	Yes	No	No
-4	343	60	0,212	No	No	No	No	No
-3	283	-60	-0,175	Yes	No	No	No	No
-2	283	0	0	Yes	No	No	-	-
-1	283	0	0	-	-	-	-	-

Graph shown on next page.

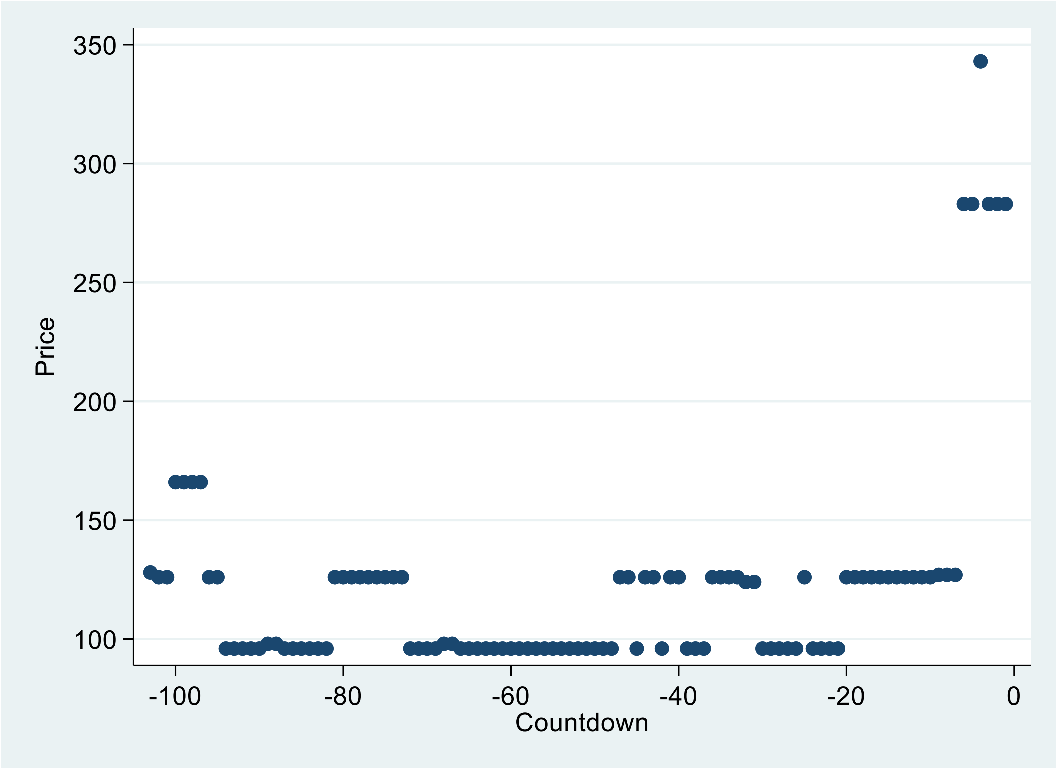

Figure 7 Graph of Price of airline tickets and Countdown for a flight on route New York (LaGuardia) - Chicago, operated by United Airlines. Assortment optimisation techniques of opening and closing of fare classes can clearly be determined through this graph. Moreover, it seems to take a considerable amount of time to establish the base load for this flight, leaving prices to sharply increase only at 6 days prior to departure. However, prices abruptly drop from $343 to $283, 3 days prior to departure and thereafter do not increase. As of this, criteria ii), iii) and iv) cannot be met.

Appendix J:

Table 7 Independent samples t-test of break points for low-cost carriers and non-low-cost carriers. The p-value of 0.0000 indicates that the group means are statistically different, at a 5%-significance level.

Independent samples t-test of break points low-cost carriers

Group	Observations	Mean	Std. Err.	Std. Dev.	95% Confidence	Interval
Low-cost carrier	485	13.480	0.342	7.532	14.152	12.808
Non-low-cost carriers	1,644	11.620	0.164	6.645	11.942	11.299
Combined	2,129	12.044	0.150	6.899	12.337	11.751

H_0: Mean Low-cost carrier = mean non-low-cost carrier
H_A: Mean Low-cost carrier ≠ mean non-low-cost carrier Pr = 0.0000

Table 8 Independent samples t-test of break points for ultra-low-cost carriers and non-ultra-low-cost carriers. The p-value of 0.0000 indicates that the group means are statistically different, at a 5%-significance level.

Independent samples t-test of break points ultra-low-cost carriers

Group	Observations	Mean	Std. Err.	Std. Dev.	95% Confidence	Interval
Ultra-low-cost carrier	127	15.315	0.715	8.059	16.730	13.900
Non-ultra-low-cost carriers	2,002	11.837	0.151	6.768	12.133	11.540
Combined	2,129	12.044	0.150	6.899	12.337	11.751

H_0: Mean Ultra-low-cost carrier = mean non-ultra-low-cost carrier
H_A: Mean Ultra-low-cost carrier ≠ mean non-ultra-low-cost carrier Pr = 0.0000

Table 9 Independent samples t-test of break points for regional carriers and non-regional carriers. The p-value of 0.0047 indicates that the group means are statistically different, at a 5%-significance level.

Independent samples t-test of break points regional airlines

Group	Observations	Mean	Std. Err.	Std. Dev.	95% Confidence	Interval
Regional airline	29	8.448	1.411	7.600	11.339	5.557
Non-regional airline	2,100	12.094	0.150	6.878	12.338	11.799
Combined	2,129	12.044	0.150	6.899	12.337	11.751

H_0: Mean Regional carrier = mean non-regional airline
H_A: Mean Regional carrier ≠ mean non-regional airline Pr = 0.0047

Appendix K:

Table 10 Pooled Ordinary Least Squares regression on Break Point with HHI, number of carriers on route and market share route carrier for Ultra-low-cost carriers.

VARIABLES	Break point (HHI)	Break point (Number of carriers on route)	Break point (Market share route carrier)
Constant	-60.18	-80.72*	-85.75*
	(42.93)	(45.76)	(44.15)
HHI_j	-7.765***		
	(2.187)		
Number of carriers on $route_j$		0.586**	
		(0.283)	
Market share of carriers on $route_{ij}$			-4.295***
			(1.484)
Ultra-low-cost $carrier_{ijt}$	-5.999	0.785	-3.616
	(3.976)	(4.963)	(2.560)
× HHI_j	10.65		
	(10.35)		
× Number of carriers on $route_j$		-0.647	
		(1.085)	
× Market share of carriers on $route_{ij}$			2.525
			(15.67)
Monthly load $factor_i$	223.6***	236.7***	241.8***
	(58.56)	(59.27)	(58.24)
Yearly load $factor_i$	-148.2***	-163.7***	-150.2***
	(52.69)	(51.87)	(53.86)
Ln(Total available seat $miles_i$)	11.09**	13.24**	12.82**
	(4.855)	(5.302)	(5.022)
Ln(Total passengers $transported_i$)	-7.974**	-9.194***	-9.084***
	(3.100)	(3.319)	(3.189)
Ln(Net $Income_i$)	-0.142	-0.315	-0.157
	(0.450)	(0.457)	(0.441)
Ln(Total $Assets_i$)	-2.799***	-3.014***	-3.035***
	(1.021)	(1.049)	(1.025)
Ln(Population Origin $City_j$)	-0.409	-0.361	-0.360
	(0.503)	(0.498)	(0.501)
Ln(Income Origin $City_j$)	0.470	1.032	0.648
	(1.345)	(1.318)	(1.309)
$Distance_j$	0.00659***	0.00583***	0.00597***
	(0.00178)	(0.00188)	(0.00186)
$Distance_j^2$	-2.31e-06***	-2.08e-06***	-2.18e-06***
	(5.53e-07)	(5.82e-07)	(5.76e-07)
Afternoon $flight_t$	-0.393	-0.396	-0.387
	(0.332)	(0.331)	(0.333)
Evening $flight_t$	-0.747*	-0.764*	-0.729*
	(0.415)	(0.413)	(0.419)
Aircraft $capacity_{ijt}$	0.000443	-0.00217	0.00453
	(0.00509)	(0.00511)	(0.00539)
Observations	2,127	2,127	2,127
R-squared	0.067	0.058	0.061

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix L:

Table 11 Pooled Ordinary Least Squares regression on Break Point with HHI, number of carriers on route and market share route carrier for Regional airlines.

VARIABLES	Break point (HHI)	Break point (Number of carriers on route)	Break point (Market share route carrier)
Constant	-32.09	-29.23	-32.63
	(43.79)	(43.58)	(44.11)
HHI_j	-5.165**		
	(2.391)		
Number of carriers on $route_j$		0.344	
		(0.303)	
Market share of carriers on $route_{ij}$			-1.911
			(1.532)
Regional $airline_{ijt}$	-1.397	-17.19**	-1.734
	(13.69)	(7.071)	(12.72)
× HHI_j	13.80		
	(18.17)		
× Number of carriers on $route_j$		-3.303	
		(3.306)	
× Market share of carriers on $route_{ij}$			-14.08
			(14.79)
Monthly load $factor_i$	128.7**	125.4**	118.1**
	(55.15)	(55.21)	(55.77)
Yearly load $factor_i$	-104.8**	-104.9**	-96.97*
	(52.14)	(51.88)	(53.45)
Ln(Total available seat $miles_i$)	-0.0572	-0.239	-0.778
	(5.466)	(5.485)	(5.424)
Ln(Total passengers $transported_i$)	-1.946	-1.804	-1.533
	(3.375)	(3.403)	(3.354)
Ln(Net $Income_i$)	0.590	0.552	0.667
	(0.481)	(0.476)	(0.485)
Ln(Total $Assets_i$)	-0.532	-0.504	-0.337
	(0.976)	(0.975)	(0.971)
Ln(Population Origin $City_j$)	-0.588	-0.598	-0.585
	(0.470)	(0.454)	(0.459)
Ln(Income Origin $City_j$)	0.612	0.991	0.820
	(1.342)	(1.297)	(1.295)
$Distance_j$	0.00504***	0.00436**	0.00431**
	(0.00178)	(0.00184)	(0.00187)
$Distance_j^2$	-1.78e-06***	-1.57e-06***	-1.57e-06***
	(5.50e-07)	(5.69e-07)	(5.81e-07)
Afternoon $flight_t$	-0.391	-0.385	-0.386
	(0.334)	(0.334)	(0.334)
Evening $flight_t$	-0.764*	-0.767*	-0.751*
	(0.416)	(0.413)	(0.416)
Aircraft $capacity_{ijt}$	-0.00365	-0.00569	-0.00330
	(0.00506)	(0.00500)	(0.00539)
Observations	2,127	2,127	2,127
R-squared	0.072	0.068	0.068

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix M:

Table 12 Pooled Ordinary Least Squares regression on Break Point, main model. Sensitivity analyses excluding conditions for determining break points as discussed in section four, methodology.

VARIABLES	Break point (Excluding condition i)	Break point (Excluding condition ii)	Break point (Excluding condition iii)	Break point (Excluding condition iv)
Constant	-26.33	-64.27	-15.80	-101.3**
	(71.63)	(47.62)	(43.65)	(48.15)
HHI_j	-11.66***	-11.00***	-9.444***	-4.717*
	(3.358)	(2.699)	(2.503)	(2.469)
Low-cost $carrier_{ijt}$	-23.10***	-2.530	-1.638	-4.905
	(6.687)	(6.017)	(5.405)	(5.839)
× HHI_j	8.222	18.10**	14.52***	10.91**
	(5.962)	(7.472)	(5.143)	(5.413)
Monthly load $factor_i$	-207.1	16.54	118.3	270.8**
	(148.1)	(119.4)	(107.9)	(119.2)
Yearly load $factor_i$	448.6***	4.681	-62.46	-180.9
	(168.6)	(139.3)	(126.4)	(136.9)
Ln(Total available seat $miles_i$)	-24.20*	-3.265	3.320	13.60
	(12.81)	(9.527)	(8.774)	(10.12)
Ln(Total passengers $transported_i$)	-6.724	-5.032	-5.962**	-9.159***
	(4.117)	(3.314)	(2.932)	(3.286)
Ln(Net $Income_i$)	5.734***	2.362*	0.883	-0.760
	(1.687)	(1.370)	(1.304)	(1.440)
Ln(Total $Assets_i$)	19.62***	4.066	0.888	-2.159
	(5.836)	(4.681)	(4.536)	(5.032)
Ln(Population Origin $City_j$)	0.185	-0.487	-0.459	-0.574
	(0.499)	(0.515)	(0.518)	(0.462)
Ln(Income Origin $City_j$)	-2.094	-1.167	0.637	0.954
	(1.290)	(1.542)	(1.328)	(1.063)
$Distance_j$	0.0124***	0.00525***	0.00641***	0.00589***
	(0.00204)	(0.00196)	(0.00174)	(0.00175)
$Distance_j^2$	-4.13e-06***	-1.56e-06**	-2.19e-06***	-2.32e-06***
	(6.32e-07)	(6.32e-07)	(5.42e-07)	(5.58e-07)
Afternoon $flight_t$	-0.392	-0.217	-0.385	-0.575
	(0.417)	(0.383)	(0.332)	(0.396)
Evening $flight_t$	-0.154	-1.638***	-0.756*	-1.110**
	(0.552)	(0.452)	(0.413)	(0.445)
Aircraft $capacity_{ijt}$	0.00563	5.76e-05	-0.000628	0.00250
	(0.00657)	(0.00624)	(0.00523)	(0.00532)
Observations	2,288	2,149	2,127	2,173
R-squared	0.089	0.088	0.071	0.064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix N:

Table 13 Pooled Ordinary Least Squares regression on Break Point, main model. Sensitivity analyses changing the values for the thresholds for number of days and cumulative percentage increase for determining break points for conditions i) and ii) as discussed in section four, methodology.

VARIABLES	Break point (No decrease for at least 5 days condition i)	Break point (An increase for at least 10 days condition i)	Break point (Cumulative increase of more than 25% in following 7 days condition ii)	Break point (Cumulative increase of more than 25% in following 5 days condition ii)
Constant	-6.955	-15.99	8.722	9.018
	(46.69)	(33.97)	(45.60)	(58.65)
HHI_j	-10.62***	-7.282***	-9.637***	-6.255**
	(2.556)	(2.089)	(2.610)	(2.636)
Low-cost $carrier_{ijt}$	4.118	-4.805	2.107	-1.046
	(5.273)	(4.878)	(5.323)	(6.695)
× HHI_j	12.69**	15.68***	12.12**	7.012
	(4.982)	(4.369)	(5.974)	(5.447)
Monthly load $factor_i$	28.17	127.3	76.88	179.5
	(107.7)	(86.95)	(109.2)	(142.4)
Yearly load $factor_i$	58.56	-104.7	-24.50	-138.3
	(125.2)	(105.1)	(127.8)	(161.1)
Ln(Total available seat $miles_i$)	-4.282	5.774	0.822	6.338
	(8.911)	(6.746)	(8.930)	(12.22)
Ln(Total passengers $transported_i$)	-5.105*	-5.210**	-6.460**	-6.694*
	(2.879)	(2.509)	(3.064)	(3.635)
Ln(Net $Income_i$)	2.078	0.466	1.518	0.301
	(1.320)	(1.078)	(1.315)	(1.690)
Ln(Total $Assets_i$)	5.113	-0.976	2.788	-0.245
	(4.478)	(3.882)	(4.514)	(5.796)
Ln(Population Origin $City_j$)	-0.536	-0.0984	-0.497	-0.450
	(0.495)	(0.362)	(0.506)	(0.480)
Ln(Income Origin $City_j$)	0.634	0.701	-0.0138	-0.0537
	(1.303)	(1.223)	(1.390)	(1.321)
$Distance_j$	0.00906***	0.00442**	0.00535***	0.00354*
	(0.00175)	(0.00169)	(0.00179)	(0.00185)
$Distance_j^2$	-3.03e-06***	-1.73e-06***	-1.80e-06***	-1.34e-06**
	(5.58e-07)	(5.54e-07)	(5.54e-07)	(5.73e-07)
Afternoon $flight_t$	-0.757**	0.0208	-0.304	-0.103
	(0.303)	(0.315)	(0.343)	(0.346)
Evening $flight_t$	-0.352	-0.460	-1.082**	-0.907**
	(0.405)	(0.370)	(0.429)	(0.437)
Aircraft $capacity_{ijt}$	-0.000824	0.00320	0.000278	-0.00561
	(0.00548)	(0.00472)	(0.00525)	(0.00590)
Observations	2,184	2,068	2,136	2,008
R-squared	0.074	0.070	0.069	0.056

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1