ERASMUS UNIVERSITY ROTTERDAM

Airline Business Models and Service Quality in the European Airline Industry

Are Low Cost Carriers More Punctual?

Master Thesis

Ann Katrin Becker
Student No. 359389
Master in Economics and Business
Specialization in Urban, Port and Transport Economics
Supervised by Peran van Reeven (Dr. LL.M.)

May 7th 2013

Abstract

This paper aims at extending knowledge of the link between airline business models and service quality. It specifically asks whether low cost carriers (LCCs) are more punctual than traditional network carriers (TNCs). Previous research has not answered this question for the European case so far. Therefore, this paper complements existing research and adds transparency and accuracy to simple on-time performance (OTP) rankings that are available on the internet. It builds on empirical evidence from more than one million intra-European flights, including flights from 8 European TNCs and 5 European LCCs. Our statistical analyses indicate that LCCs are more punctual than TNCs. At the same time, we have to expect that the overall OTP advantage of LCCs is the result of a heterogeneous set of individual airlines' performances. Thus, generalizing our findings to other airlines is problematic.

Table of Content

1 Introduction

This paper investigates the connection between airline business models and service quality in the European airline industry. It builds on current academic literature as well as empirical evidence from more than one million intra-European flights, including flights from 8 traditional network carriers (TNCs) and 5 low cost carriers (LCCs). Based on this sample we want to find out: do LCCs provide significantly better service than TNCs?

In our analysis we use airlines' on-time performance (OTP) as a measure of service quality. The reason behind is that poor OTP is what most customers complain about (Mazzeo, 2003). By investigating OTP we focus on service aspects that are non-visible while booking. Whereas the customer is able to judge about an airline's scheduled travel time while booking, he remains uncertain about the actual reliability of that airline. We measure this reliability in two ways: first, we use scheduled (arrival) times as reference for OTP; and second, we refer to the shortest travelled time on a particular route. Both are compared with actual (arrival) times on individual flight level. We introduce the shortest travelled time because the scheduled time are posted by airlines themselves, indicating that airlines can easily manipulate OTP. We use a statistical approach to analyse our data. With the help of two-mean comparisons and regression analyses we will test some dedicated hypotheses.

Equally relevant is the question of why we suspect a difference at all in LCCs' and TNCs' service quality. Basically, we start from two different lines of reasoning. First, research reveals that expectations about product or service quality tend to be linked to price levels. Accordingly, we assume that certain passengers have prejudices about LCCs' OTP. We want to reassess and test these prejudices. Another argumentation starts from an operational perspective, suggesting that punctuality is fundamentally inherent in the uncomplex LCC business model. Certain business model choices, such as the one to mainly operate to and from uncongested, secondary airports, are expected to have a positive effect on OTP.

There are publically available rankings that evaluate airlines according to their OTP. However, these rankings make rather rudimental judgments. A set of rankings from private companies consistently receives attention. These rankings mainly compare the share of on-time flights across airlines. Their method simplifies a complex situation of various factors interacting with each other. It neglects, for instance, that some airlines depart and arrive from airports that are supposedly more difficult to land in. In fact, it is problematic to "evaluate players who compete in overlapping but not identical tournaments" (Caulkin et al., 2012, p. 710). It has been shown that airport difficulty makes a difference in the airlines' OTP scores (Caulkin et al., 2012). Thus, a simple mean comparison of OTP rates between LCCs' and TNCs' OTP without investigating the circumstances is not sufficient. Instead we are curious about what happens when we compare LCCs and TNCs under similar circumstances.

Despite – or probably because – of their simplicity, rankings are often cited in the news or airlines' marketing campaigns. Only in this year, quite a few well-known newspapers referred to air traffic statistics firm FlightStats. FlightStats' "On-time Performance Service Awards" recently announced Scandinavian Airlines to be Europe's most punctual airline, outperforming KLM and Ryanair on second and third position. Partly decoupled from these results, airlines aggressively market their allegedly high punctuality. For instance, together with each of Ryanair's monthly traffic statistics there is a comment on the website, announcing Ryanair to be Europe's No.1 on-time airline – supposedly beating easyJet in OTP every week since 2003.[1]

With our analysis we aim at adding transparency and accuracy to the discussion about airlines' OTP. We achieve this by using regression models that estimate the overall LCC effect and individual airline-specific effects while controlling for airport variables as well as economic, logistical and weather variables. Thereby, we find out to whether the potential LCC OTP advantage is simply rooted in airport and route choice.

We believe that our research is important due to several reasons. First, in academic research the European case of this topic is relatively understudied. No paper before has particularly investigated the difference in OTP between European LCCs and TNCs on individual flight level. Second, delays have serious cost implications[2]. Delays induce costs not only for passenger, but also for society at large and, of course, for airlines. Since a more stringent European passenger bill of rights came into force in 2004,

[1] In another press release Ryanair states: "Yet again EasyJet are unable to match Ryanair's prices or our industry leading punctuality. We again call on EasyJet to resume publishing monthly punctuality stats on its passenger website instead of hiding their abysmal performance in quarterly investor reports. EasyJet can't compete with Ryanair's low fares or punctuality which is why millions more passengers prefer to fly on Ryanair's low fare, on-time flights than on EasyJet's high fare, frequently delayed flights" (Ryanair, 2011)

[2] For an intensive overview of costs of delay we recommend Cook and Tanner's (2011) research.

airlines of all types are obliged to compensate passengers in case of cancelled, diverted or extensively delayed flights[3].

We proceed with our research according to the following structure. Section 2 clarifies how we understand OTP in this paper. Moreover, we will consult previous research to investigate determinants of flight delays. Section 3 then provides a historical perspective on the European airline industry, describing how LCCs have emerged. The section then outlines the characteristics of the LCC business model and puts it into the context of OTP. Afterwards, section 4 draws on the research design. The results of the research are then presented in section 5. The final section contains the conclusion.

[3] "In the event of long delays, the airline has to offer meals, refreshments, hotel accommodation if necessary, and means of communication. If the delay exceeds 5 hours, it has to propose refunding the ticket (with, if necessary, a free flight to your point of departure)" (European Union, 2005)

2 Airline On-Time Performance

There are quite a few papers on service quality and OTP. The insights from that will be highly valuable for our research design. The papers mainly answer three broad research questions: (1) What are accurate OTP metrics? (Caulkins et al., 2012; Thrasher & Weiss, n.d.; Wang, 2007; Sherry, Wang, Xu, & Larson, n.d.) (2) What are sources and effects of delays? (3) How do delays propagate in the network? (Beatty, Hsu, Berry, & Rome, 1998; Wang, 2007). In section 2.1 we present papers that relate to the first question. The vast majority of articles, however, covers the second question. Their findings are included in section 2.2[4].

2.1 Definition of On-Time Performance

There are a number of different indicators that help to evaluate airlines' OTP. This section aims at shedding light on the existing definitions and measurements of OTP, delays and other related terms, outlining them in the context of air transportation.

The measurement of OTP actually depends on the perspective taken. Still, most OTP measures share a common aim: they intend to measure whether – or to what extent – operations comply with an airline's time schedule. Strictly speaking, they detect any deviation from a schedule – be it positive or negative. However, from a consumer's perspective it seems irrelevant whether a flight arrives a few minutes too early or perfectly on-time, as long as it is not delayed. Therefore, focus of our research is not on schedule deviation (positive, zero or negative) but on delay (zero or positive). This way of evaluating OTP is reasonable from a passenger's viewpoint. However, from an operational perspective "early" flights are equally relevant. They induce significant costs for airlines, too (Performance Review Commission, 2012). However, we neglect this and keep focussing on delays.

Moreover, we assume that consumers focus on OTP at arrival as we mentioned before. A flight may be delayed at departure but still be perceived as a high quality service when it at least arrives on-time. Thus, consumers mainly evaluate OTP based on the

[4] Section 2.2 will only investigate the source ("determinants") of delays. For research on the effects of OTP check the following papers. For instance, scholars explore the effect OTP itself has on market share (Suzuki, 2000), ticket fares (Forbes, 2008), customer satisfaction (Steven, Dong, & Dresner, 2011) or airline profitability (Dresner & Xu, 1995). Again others quantify hard and soft costs that result from delays (Kingdom, Tanner, Enaud, Expert, & Unit, 2010; Cook, 2010).

question: does the flight arrive latest at the scheduled arrival time that I agreed with during booking?

Whether or not a flight arrives “on-time” is a widely accepted OTP indicator that also links to what we just said about the customer’s quality assessment. In that case arriving “on-time” does not necessarily require perfect adherence to timetables. Instead, customers may still be satisfied when the flight arrives with only a short delay. Accordingly, flights with a delay of x minutes compared to the schedule are still considered “on-time”.

Those who are professionally concerned with OTP, usually allow for 15 minutes of delay. This indicator is also known as D+15 OTP (Wu, 2005). With respect to the allowance, it is expected that short delays of below 15 minutes still ensure operations to run smoothly (Röhner, 2009) and passengers to carry on their connecting journey or other activities as planned. We appreciate the D+15 in our research because of its compactness. Two of the most prominent users of D+15 are the U.S Bureau of Transportation Statistics (BTS) and the Central Office for Delay Analysis (CODA), a service of EUROCONTROL. But also scholars and other stakeholders in the industry adopted this metric.

The D+15 is eligible, but remains debatable. There are two drawbacks: first, the on-time allowance of 15 minutes is considered arbitrary (Rupp, 2001; see Brons & Rietveld, 2007 for rail); and second, D+15 as single measurement obscures important information. Analogous to what Skagestad (cited by Olsson & Haugland, 2004) notes on rail OTP measurement, the indicator mainly suffers from its lacking distinction between small and large delays. There are no weights attached to different magnitudes of delays (Brons & Rietveld, 2007) – as long as the delay is above the defined allowance, it is recorded as such.

As a solution to this reporting problem there are two approaches available. The first approach comprises a number of different allowance levels (e.g. 5, 10, 30, 45 minutes). Such differentiation is justified because the individual perception of punctuality differs from passenger to passenger, with some being stricter and some more forgiving than others (Rupp, 2001). Moreover, for intra-European flights smaller allowances are useful as the 15 minutes allowance usually makes up a considerable fraction of scheduled block time (Performance Review Commission, 2012). In line with this, CODA and the BTS report on the share of punctual flights also using other allowance levels than 15 minutes, too. The second approach, which CODA and BTS also follow, is the usage of the arrival delay in minutes. This is probably the most straight forward measurement of OTP. Still, it needs to be kept in mind that when calculating average delays these averages are over-sensitive to largely delayed flights, which only reflect an extremely small share of total flights (Spehr, 2003).

We conclude that for our research two OTP indicators are essential: (1) an indicator that measures the occurrence of delays (2) another indicator that measures the magnitude of arrival delays.

All measures that we introduced so far use the respective airline's scheduled arrival (or departure) time as a reference. Certainly, this is justified because consumers agree with – and therefore trust in – the indicated times. However, in our study we want to go beyond that. We are aware that airlines can to some extent actively influence their OTP by artificially stretching scheduled flight times. The schedules are subject to so called "schedule padding", which means that airlines anticipate some strategic delays by adding buffer times to realistic travel times. When we now compare LCCs' and TNCs' OTP we want to account for this potential manipulation.

Mayer and Sinai (2002) suggest an alternative OTP indicator that is unaffected by airlines' scheduling decisions: so-called excess travel time. Excess travel time measures the difference between actual travel time and the shortest feasible travel time. Mayer and Sinai define the shortest feasible travel time as " the shortest observed travel time on a given nonstop route in a particular month" (Mayer & Sinai, 2002, p.17). As opposed to that, ordinary delay measures compare actual and scheduled flight times.

Rupp (2007), who replicated Mayer and Sinai's approach for his regression analysis, adds some important points to the discussion about excess travel time. He remarks that the variable provides accurate information on how long it takes for an airline to transport passengers in the absence of air traffic congestion. At the same time, excess travel time does not account for the different characteristics of individual flights that run on a specific route, which is a major disadvantage of this measure. For instance, using the route's monthly minimum travel ignores differences in the aircraft's type and capacity (Rupp, 2007). Furthermore, it neglects that some flights take place at peak times whereas others operate at rather quite time slots.

To conclude, we will mainly use three measurements of OTP: the arrival delay in minutes (*delay_min_a)*, an arrival delay dummy (*del>=1_01_a* or *del>=15_01_a)*, and excess travel time in minutes (*excess_min*). We define our three OTP measurements as follows:

Variable Name	Variable Description	Computation
delay_min_a	Arrival delay in minutes	*delay_min_a = scheduled arrival time – actual arrival time* with *delay_min_a* ≥ 0 (early arrivals are classified as zero minutes arrival delay)
del>=1_01_a *del>=15_01_a*	Whether the flight is 1 (15) or more minute(s) delayed at arrival	$del >= 1(15)\_01\_a = \begin{cases} 1 & for\ delay\_min\_a \geq 1(15) \\ 0 & for\ delay\_min\_a < 1(15) \end{cases}$
excess_min	Difference between actual travel time and the shortest feasible travel time (same route and month)	*excess_min* = *actual travel time – shortest feasible actual travel time of the same month + delay_min_d* with *delay_min_d* analogous to *delay_min_a* but at departure and with *actual travel time = actual arrival time – actual departure time*

Table 1: Three Main Delay Variables

2.2 Determinants of On-Time Performance

OTP as measured above is the end result of a myriad of influencing factors. Operations are part of a complex system of interaction between different stakeholders, such as airlines, airport operators and air traffic flow management (Performance Review Commission, 2012). To understand relationships between various factors and OTP this section presents a short review of current literature.

For daily OTP reporting, the IATA introduced a standardized set of delay codes for delay causes. Around ninety delay codes help to classify delays according to their cause (see Appendix A). Basically, the IATA distinguishes between primary delays and so called reactionary delays, which originate from primary delays of previous flights. According to statistics of 2011 almost half of all delays can be attributed to delay propagation (Performance Review Commission, 2012, p.15).

Yet, simply reporting delay codes is not sufficient to get further information about what we might control for. Current academic literature complements the picture on delays. Mostly analysing large samples of individual flights with statistical methods scholars try to better explain the determinants of delays. Their papers' regression models control for similar variables. Some of these variables are included in a simplified list below[5] and shortly described afterwards. To a large extent we aligned the separation into four categories with Rupp's research. We will now check the findings for each of the categories.

Airport Variables	Existence and size of hub airport at origin and destination Existence and size of the operating airline's hub at origin and destination Level of slot coordination
Economic/Competitive Variables	Route yield Route load factor (and seating capacity) Duopoly/Monopoly route Market share route Airport concentration
Logistical Variables	Distance Departure time Day of week Season/month Aircraft type/age
Weather Variables	Temperature Precipitation Snow/thunder/rain

Table 2: OTP's Influencing Factors

Airport Variables

Hub effects are significant determinants of delays. Scholars distinguish between hub airport effects and hub airline effects. They mostly control for both, using dummies according to hub size. Concerning hub airports, Rupp (2009) finds for the U.S. the same as Santos and Robin (2010) do for Europe: delays at hub airports are larger than at non-hub airports. Santos and Robin add to their finding that delays do not increase monotonically with hub size. Instead, arrival delays are said to be lower at medium hubs compared to big hubs but also compared to small hubs.

[5] Category titles "airport variables", "economic/competitive" and "logistical variables" adopted from Rupp (2007). Variables assigned to each category differ from Rupp (2007).

In another study, Rupp (2007) argues that is not the existence of hub airports that is decisive. Instead *airline* hub size is the primary source of delay. Mayer and Sinai (2002) shortly describe the duality of airlines hubs: on the one hand, airlines benefit because cross-connection of passengers increases the number of markets served and load factors; on the other hand, airlines have to face additional costs of delays.

However, the effect of airline hubs on delays is not as straight-forward as indicated by Mayer and Sinai. In fact, findings are mixed. Rupp & Sayanak (2008) and Rupp (2007) find that delays are significantly longer when the flight operates from / to the operating airline's own hub. Larger airline hubs cause longer delays. Some scholars find opposite results (Mazzeo, 2003; Santos & Robin, 2010). Santos and Robin try to find explanations for the negative coefficient in the European setting. They assume that the hub-and-spoke system in Europe, the subject of their investigation, is not as extensive and more constrained with respect to slot coordination as the U.S. counterpart that is under investigation in Rupp's research.

If we like to learn how OTP varies across airlines, we also have to consider that airlines only have limited freedom in scheduling their flights. Santos' & Robin's (2010) include variables for slot coordination because slot coordination is a common feature in Europe compared to the U.S. In fact, at capacity constrained airports, slot coordination restricts airlines in their freedom to schedule flights. European airports are divided into three categories: non-coordinated[6], schedule facilitated[7] and coordinated[8].

Regressions show mixed results on the effect of slot coordination, depending on whether origin or departure airports are under investigation and which sample (e.g. only coordinated airports) is used. Including all airports, however, indicates that OTP at origin airports decreases with the level of slot coordination. Also Rupp (2009) considers slot coordination in this research about the internalization of delays. Similar to Santos and Robin he also creates sub-samples of airports according to their level of slot coordination. In particular, he performs robustness checks on a sample of non-restricted

[6] A level 1 airport is defined as "a non-coordinated airport is one where the capacities of all the systems at the airport are adequate to meet the demands of users" (IATA, 2010, p.5).

[7] A level 2 airport is defined as "a schedules facilitated airport (Level 2) is one where there is potential for congestion at some periods of the day, week or scheduling period, which is amenable to resolution by voluntary cooperation between airlines and where a schedules facilitator has been appointed to facilitate the operations of airlines conducting services or intending to conduct services at that airport" (IATA, 2010, p.7).

[8] A level 3 airport is defined as "a coordinated airport (Level 3) is one where the expansion of capacity, in the short term, is highly improbable and congestion is at such a high level […]" (IATA, 2010, p.11).

airports. He considers the findings informative as they reveal how carriers behave if they are fully free in using the slots they desire.

Economic/Competitive Variables

Route load factor, route yield as well as seating capacity are often used as explanatory variables for delays. Research reveals that load factors and seating capacity have significant effects on delays. Not surprisingly, Rupp and Sayanak's (2008) study reveals: the higher the load factor the longer arrival delays are. It seems natural that loading a crowded airplane is more vulnerable to delays. Rupp and Sayanak also control for seating capacity and point out that delays increase with seating capacity. However, their motivation to include seating capacity comes from another direction: they argue that delays that happen to a larger aircraft usually affect more passengers than in the case of smaller ones. In view of the assumption that airlines intend to minimize customer inconvenience they avoid poor OTP with planes that carry many passengers. This is why seating capacity may be categorized as "economic".

Similarly consistent are the findings about the effect of yields. Obviously, OTP is higher on more profitable routes (Rupp & Sayanak, 2008; Rupp, 2007; Rupp 2001). Some explains this with the assumption that airlines are profit-maximizers that try to retain customers especially on high-fare, profitable routes.

Various types of competitive variables help to explain delays. Most of them aim at capturing the level of competition either at airports or on routes. As a measurement of competition in most cases either the Herfindahl Hirschman index[9] or a dummy for the existence of monopoly or duopoly routes are put in place.

The overall effect of competition remains unclear – the findings are not fully consistent. A number of scholars find evidence that delays are significantly shorter at more concentrated airports. Put differently, airports that are dominated by a small number airlines (or even just one) have better OTP (Mayer and Sinai, 2003a; Brueckner, 2002; Rupp & Sayanak, 2008). Others disagree and find that airport concentration (at origin) and delays are positively correlated (Rupp, 2009; Rupp, 2007).

Next to competition right at the airport, competition on routes is of major interest. Mazzeo's results indicate that OTP is relatively poor on monopoly routes. As

[9] Burghouwt, Hakfoort, & Ritsema van Eck (2003) list some alternative concentration measures.

competition increases Mazzeo expects delays to decrease. Rupp and Sayanak, however, report more differentiated results. They find evidence that is adverse to Mazzeo's findings. They explain their adverse finding by the fact that there might be better OTP on monopoly routes when these routes connect less congested or smaller airports. In another paper, Rupp (2001) claims that monopoly routes have better OTP since the monopolistic airline presumably has more freedom when it comes to scheduling.

Logistical Variables

Some studies include individual flight data and, thus, are able to control for day-of-week effects. EUROCONTROL (Performance Review Commission, 2012) collects such data and reports higher average delays on weekends. Increased traffic demand on weekends combined with limited staff available may explain this increase in delays on weekends. Mazzeo (2003) adds that mainly Fridays suffer from higher demand, whereas the Saturday is a less busy travel day. According to him, Saturdays are comparable with Tuesdays – as flights are more likely to be on-time.

Similar to the effect of particular days, arrival or departure hours have a significant influence on OTP. Scholars find considerable evidence, indicating that delays accumulate during the day and, thus, tend to be longer at later hours (Rupp & Sayanak, 2008; Rupp, 2007). By way of illustration, Mazzeo (2003) remarks that a morning flight at 8 am is usually nine minutes less behind schedule than a flight scheduled at 8 pm.

Other logistical effects involve seasonal effects. Sometimes seasonal variables are included to indirectly capture weather effects. Plausibly, weather varies by season with poor weather usually occurring at winter time. At the same time, the summer season is a busy travel season and therefore prone to delays. Rupp's (2009) investigation of monthly average delays over period of twelve years highlights that: month with most delays are December and January; fewest delays occur mainly in September and October.

Distance from origin to destination is another useful explanatory variable. It is expected that the longer the distance is, the higher is the chance for a pilot to make-up departure delays by higher speed (Rupp, 2001). In line with this, Rupp (2007) as well as Rupp and Sayanak (2008) find that longer flights have on average slightly less arrival delays.

Rather exceptional is the inclusion aircraft specific variables. Aircraft specific effects comprise age of the aircraft, type of aircraft (Boeing vs. Airbus) and sometimes – if not included already as economic variable – seating capacity.

Weather Variables

Weather is a significant predictor of OTP. Airport operations are vulnerable to strong winds, low visibility, freezing conditions or snow. A temporary cut in capacity is the result (Commission, 2005). As expected, poor weather conditions cause significantly longer delays (Rupp & Sayanak, 2008). On days with thunderstorms, the chance of long delays is particularly high. On average, flights on such days are estimated to be twelve minutes late (Mazzeo, 2003). Frost, as compared to that, requires additional treatment of runways and airplanes. Typically, airports are responsible to put maintenance and de-icing teams in place (Performance Review Commission, 2012). At the same time, special winter schedules help to account for delays in advance (Performance Review Commission, 2012).

Schedule Padding

All the presented findings measure to what extent different factors influence OTP. Nonetheless, as indicated before, schedules partly account for delays already. Embedded buffer times allow airlines to still comply with their schedule even in case of small-scale irregular operations. This process is also known as schedule padding.

Nonetheless, airlines' incentive to include buffer times is limited. Airlines' incentive to maximize fleet utilizations due to economic reasons counteracts to schedule padding (Wu, 2005). Wu notes that the delay difference between an ideal scenario of zero delays and the reality constitutes so called inherent delays which then reflect an airline's schedule planning philosophy.

EUROCONTROL (Performance Review Commission, 2012) expresses it in other words by saying that the level of schedule padding reflects an airline's strategy and its OTP targets. If true system performance – instead of inconvenience for passenger – is in focus of investigation, schedule padding should be considered in the analysis. Accordingly, scholars often use excess travel time as presented in chapter 2.1 as a measure of delay that allows isolating an airline's true operational performance.

3 The Low Cost Segment in the Airline Industry

The evolution of the low cost segment in the U.S., Europe and elsewhere arguably marks a drastic shift in the recent history of air transportation (Lee, 2003). When markets where growing rapidly and liberalization progressed, more and more LCCs ermerged. Today, passengers are often free to choose between TNCs, some smaller regional carriers and, of course, LCCs. The next section examines how LCCs have emerged in Europe and presents the current status of this development as well as an outlook to challenges faced by that carrier type. Section 3.2 then outlines LCCs' business models. Resting upon chapter 2.2, we will derive implications for OTP.

3.1 The Emergence of Low Cost Carriers in Europe

By all means, the low cost segment in the European domestic airline industry has gained dramatically in market share. Markets prior to EU traffic liberalization were fully dominated by TNC. Then in the late 1990s, when any airline with a valid Air Operator Certificate could enter the intra-European market (Gillen & Lall, 2004), competition became price-based and balance of power shifted.

Ryanair was one of the first LCCs to step in. Existing already years before and close to bankruptcy in the early 90s (Casadesus-masanell & Ricart, 2010), the airline fundamentally changed its business model towards simple and cheap itinerary. Apart from easyJet, which started operating in 1995 (Williams, 2001), a number of other LCCs have emerged since then.

In a continuously growing market, the LCCs collectively succeeded in siphoning off market shares of TNCs. While LCCs' share of total seat capacity within the European market was around 14% in August 2003, in August 2012 38% of passengers were transported by LCCs (OAG, 2012). Accordingly, the overall market grew slower than the LCC's market share. The largest players are still Ryanair and easyJet, serving around 78 and 58 million passenger yearly respectively[10] and covering a large geographical scope.

Despite their fast growth, LCCs are increasingly confronted with challenges. For example, the clash between carrier types has led TNCs to cut their fares on routes of direct competition as also Ito and Lee's (2003) research about the U.S. market finds

---

[10] Figures from 2011. Derived from the airlines' websites.

out. Moreover, some TNCs such as British Airways and KLM responded to competitive confrontation by establishing their own low-cost subsidiaries Go Fly and Buzz. Also other TNCs entered competition in the low cost segment[11].

Another challenge is a stagnation of market growth for the low cost segment in Western Europe. Compared to August 2011, in August 2012 there where around 6,000 low cost flights less and almost 700,000 seats less. But at least Eastern Europe constitutes a ray of hope for LCCs and other airlines. With yearly growth rates in LCC seating capacity of almost 190% this market remains a major opportunity for future growth. We conclude that competition between LCCs and TNCs remains rough and it certainly also covers service quality.

3.2 Low Cost Business Models and their Implications for On-Time Performance

Years before Ryanair put its low cost service into operation, Southwest Airlines pioneered in the U.S. with the first low cost business model of its kind. Essentially, the idea was to provide simple point-to-point services on short-haul urban markets that were carried out at high frequency and at low fares (Gillen & Lall, 2004). While Southwest was the first LCC ever, Ryanair is probably the airline that adopted Southwest's idea in the most extreme way (Tretheway, 2004).

Ryanair and other LCCs clearly follow the guiding principle of simplicity – or as Gillen and Lall (2004) phrase it in "simplicity of product design, simplicity of processes and simplicity of organization" (p.50). Accordingly, LCCs stick to the leitmotiv "no-frills". There is no business class or first class, no assigned seats, no food on board or checked baggage without extra charge, no frequent flyer programme and online-only ticket purchase. In the case of Ryanair there is even a fully standardized fleet.

Business model choices have consequences – also with respect to service quality. From an operational perspective, the simplicity approach as stated by Gillen and Lall (2004) may facilitate good service quality compared to operations in the complex world of TNCs. Concerning passenger perception, however, the low fare policy is an important

[11] Lufthansa, for instance, which already has its low cost subsidiary Germanwings in place, is currently planning another LCCs under the codename Direct4U. In view of this development, experts warn about brand dilution and cannibalization of the parent airline's traffic (Graham & Vowles, 2006). So, until now, the long-term future of the so-called "carrier-within-carrier" segment remains unclear.

quality indicator if no other information is available (Zeithaml, 1981; Olander, 1970). Accordingly, Casadesus-Masanell and Ricart (2010) point out that Ryanair's low fares create low expectations about service quality.

The price quality association is also what Rupp and Sayanak (2008) inspired to conduct their research "Do Low Cost Carrier Provide Low Quality Service?". With their research they fill a void in literature that addresses the OTP of LCCs. By analysing around than six million domestic flights in the U.S. they show that LCCs are slightly less delayed than their non-LCC counterparts. They also indicate that the strong performance of LCCs is mainly driven by the performance of Southwest Airlines, given that the airline has a large market share in the LCC segment. The strong OTP of Southwest, again, is found to be embedded in the low cost business model: Southwest operates only point-to-point, uses only a single aircraft model, lacks transit passengers and serves less congested airports.

Unfortunately, for the European airline industry no similar research exists. Some European studies that we mentioned in chapter 2.2 control for carrier fixed effects; but do not report on the results (see Santos & Robin, 2010) – neither do they group carriers into types of carriers as Rupp & Sayanak (2008) did. The European research of Santos & Robin also uses for every flight the average delay values of the corresponding route and carrier during the respective season as dependent variable. Due to this, they are not able to explicitly control for factors on individual flight level, such as departure time. In fact, LCCs' tendency to schedule flights out of peak times is another approach to avoid congestion which is at the edge of the LCC business model choice and tactics is.

Certainly another influencing factor for OTP is the level of competition LCCs usually face. When recalling chapter 2.2 we find that competition may influence OTP – although there is no consensus among scholars about the sign of this effect. In fact, the level of competitive confrontation of LCCs is not explicitly embedded in the business model but somehow resulting from it. Serving many secondary airports, LCCs do hardly ever face perfect competition with TNCs. Gillen and Lall add to that due to Ryanair's fast expansion the airline has a first mover advantage. Even other LCCs operating from secondary airports avoid face-to-face competition. As a consequence, LCCs sometimes hold a monopolistic position on routes, such as Ryanair, for instance, does on routes like to and from Magdeburg Cochstedt or Hamburg/Lübeck. Having a monopolistic position may take out pressure for LCCs to be on-time.

Yet, there are also elements in the business model that may result in as competitive disadvantage with respect to OTP. Firstly, outsourcing is particularly prominent in the Ryanair business model, which reduces control and may compromise OTP (Gillen & Lall, 2004). Similar to EasyJet, Ryanair outsources everything except of cabin crew, pilots and management functions. Ground handling and to some extent maintenance are handed over to subcontractors. In this light, Ryanair’s penalty and reward system for subcontractors may have a compensating effect. Secondly, the fast turnaround, which LCCs are famous for, may jeopardize OTP. Even though fast turnaround increase aircraft productivity, it may also put OTP in danger as schedules have less delay absorption ability (Wu & Caves, 2003).

4 Research Hypotheses

Based on the preceding literature review we define five hypotheses that are to be tested. All hypotheses refer to the European airline industry. We restrict our interest to Western European airlines and intra-/Western-European point-to-point services.

Essentially, the findings from chapter 3.2 suggest that LCCs' business models contain some distinct features that may lead to better OTP. To recapture, some of these features mainly involve LCCs' airport choice, route choice and scheduling decisions. Thus, we state our first hypothesis as follows:

> **Hypothesis 1:** *Given LCCs' airport, route and scheduling choices, LCCs have shorter arrival delays than TNCs.*

Our literature review revealed that airlines may manipulate their OTP by including large buffer times. We did not find much evidence from other research about differences in scheduled travel times on comparable flights between LCCs and TNCs. Notwithstanding; we want to find out whether there is such difference. In this light, we propose hypothesis 3 as follows:

> **Hypothesis 2:** *There is a significant difference in scheduled travel time between LCCs and TNCs which indicates that on average one or the other carrier type tends to include more buffer time.*

In fact, hypothesis 1 reflects an approach that is very similar to the rankings that we criticized before: it asks for a comparison of OTP between LCCs and TNCs while ignoring all other factors that may have an influence on OTP. Starting from that, we are curious whether there is still a significant difference in OTP when we control for some influencing factors. Accordingly, we arrive at our second hypothesis.

> **Hypothesis 3:** *Even after controlling for airport size, competition and other factors, LCCs still register shorter arrival delays.*

We will carefully reflect hypothesis 3 in the context of hypothesis 2. Next to that we will introduce a measure of OTP that is unaffected by schedule padding. Chapter 2.1 introduced excess travel time which we adopt in our analysis. We simply rephrase hypothesis 3 by swapping arrival delay with excess travel time. This leads to hypothesis 4:

Hypothesis 4: *After controlling for airport size, competition and other factors, LCCs register shorter excess travel time.*

Until now, hypotheses 1 to 4 checked differences between the two carrier types. Hypothesis 5, on the other hand, is concerned with airlines' individual performances. It answers the question of how individual airlines drive the overall LCC effect and whether the group of LCCs is rather homogenous or heterogeneous. Hence, it states:

Hypothesis 5: *The overall LCC OTP is driven by a homogenous set of individual OTP.*

5 Research Design

This chapter describes how we will test our 5 hypotheses. Essentially, we use a statistical approach, analysing flight data from Europe. At first, section 5.1 explains which OTP data we have at hand. It also explains how our sample has been selected, collected, and revised. Section 5.2 then outlines the statistical methods that we use. Section 5.2 also contains an overview over our variables.

5.1 Data Collection and Sample Selection

Generally, there are two types of sources of OTP data available: (1) governmental institutions (2) international organizations and private companies. Whereas major U.S. carriers are obliged to report OTP data to the Bureau of Transportation Statistics, European airlines are not confronted with such regulation. Notwithstanding; this paper requires European data.

Currently, the best source for European delay data is EUROCONTROL. EUROCONTROL collects data and provides statistics and forecasts on European air traffic for more than 10 years now. Yet, neither is EUROCONTROL part of official institutions (e.g. EU), nor is reporting by airlines mandatory. Moreover, only aggregated delay data is available to the general public. Access to other data is only allowed to those professionally engaged in Air Traffic Flow Management and aircraft operations.

For Europe, other private data providers serve as an alternative. This analysis is carried out based on the OAG's Historical Flight Status Database. OAG provides individual flight data and documents scheduled and actual departure/arrival times. As a reliability check, we consult a separate data set of FlightStats, another private data provider. A randomly selected set of twenty flights shows a 95% match of data. Dobruszkes (2009) also attests the quality of OAG data by comparing OAG data with data from national statistics and data published by airlines. Actually, this is not a surprise, because we expect data providers to collect their data from similar sources, namely direct airline and airport data feeds.

From the OAG database we obtain a first sample that includes all non-stop flights of Western Europe's largest airlines between April 2012 and September 2012. Airline size is defined by the amount of passengers carried and figures are included in Appendix B. We include 13 airlines in total – 5 LCCs and 8 TNCs. The LCC group contains easyJet

(U2), Ryanair (FR), Norwegian (DY), Air Berlin (AB) and Vueling (VY). TNCs are represented by SAS (SK), Swiss (LX), Lufthansa (LH), KLM (KL), Iberia (IB), British Airways (BA), Alitalia (AZ) and Air France (AF). Including at least 5 airlines of each type ensures that our inferences are conclusive and transferrable to other airlines beyond the sample. We make sure not to include the low cost affiliates of TNCs. Charter or cargo flights are not part of the sample.

We want to highlight that the included LCCs share some common characteristics; but are, of course, not fully identical. These similarities and differences, do, on the one hand, justify a group comparison of LCCs and TNCs later in our analysis, but, on the other hand, also call for the investigation of OTP of individual LCCs. We will come back to this point later.

We chose the sample period because of four main reasons. Firstly, data from 2012 gives an up-to-date picture of delays. Secondly, a period of six months depicts a manageable sample size. Thirdly, focus of this research is on variation over airlines or carrier types and not on variation over time. Fourthly, we clearly exclude severe winter weather in December, January, February and partly March. Investigating the effect of all kinds of weather conditions is not the primary intention of this study.

As a next step, we further reduce the sample in accordance with specific sample selection criteria. We omit all flights that have a missing reported departure status or reported arrival status. Cancelled and diverted flights are also excluded. For codeshare flights only the flight of the airline that actually operates the flight remains in the sample. For specific days, that are subject to large scale disruptions, such as bomb disposals or major construction works, we neglect the affected airports' data for that day. As a last step we detect obvious mistakes in OAG's reporting and coding. To give two examples, we omit flights where the actual departure time equals the actual arrival time or where flights arrive exorbitantly early or late[12].

We consider flights from airport X to airport Y as different markets than the other direction from Y to X. In line with that, Mayer & Sinai (2002) argue that there may be different wind directions as well as other physical differences which justify separate treatment. Furthermore, arrival at a particular airport may be significantly different from

[12] We exclude flights that either depart one hour or more minutes to early, or arrive 6 hours or more too late.

departure at the same airport. For these reasons, we keep all routes' flights into both directions in the sample. Thereby we follow Borenstein (1990), Mayer & Sinai (2002), Berry (1990) and Rupp (2001). As against, the sample of Rupp and Holmes (2006) include flights only in one direction to avoid correlation. As a result of our adjustments the final sample contains 1,056,842 individual flights. Based on this sample, we want to test our hypotheses.

5.2 Statistical Approach and Underlying Measures

We use five customized statistical methods to test the five hypotheses. The schematic figure below (see Figure 1) illustrates each of these methods.

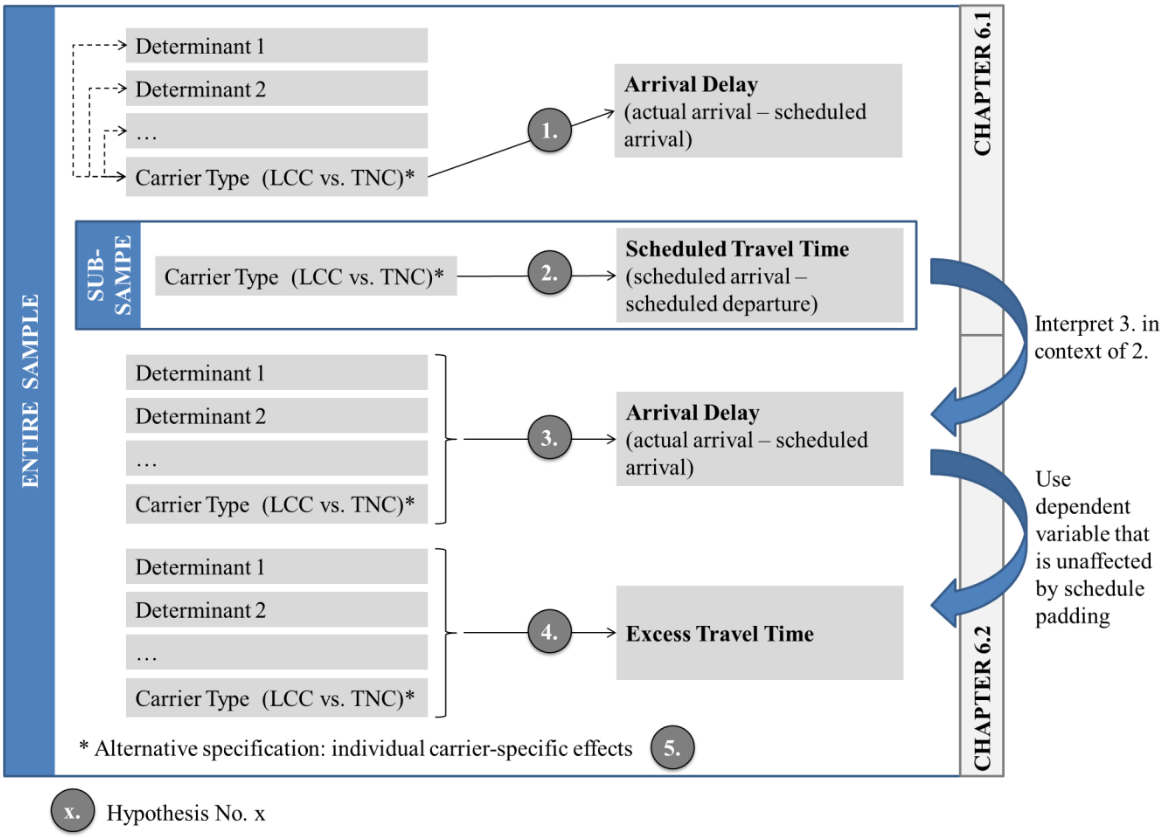


Figure 1: Statistical Approach

Hypothesis 1

The hypothesis stated: "*given LCCs' airport, route and scheduling choices, LCCs have shorter arrival delays than TNCs.*" It calls for a simple mean comparison in arrival delay between LCCs and TNCs, which is illustrated at the top of Figure 1. We use the variable *delay_min_a* to measure arrival delay and compute it as mentioned in chapter 2.1. As said before such an isolated mean comparison ignores all other factors that may have an influence on arrival delay. The results are included in chapter 6.1.

Hypothesis 2

Either confirming or rejecting hypothesis 2 is necessary for our conclusion about hypothesis 3. The hypothesis addresses whether *"there is a significant difference in scheduled travel time between LCCs and TNCs which indicates that on average one or the other carrier type tends to include more buffer time."* We also conduct a two-mean comparison between LCCs and TNCs, this time comparing scheduled travel time. We measure scheduled time as indicated in chapter 2.1 (*sched_travelt_min*). Chapter 6.2. contains the results.

We are aware that a mean comparison across all kinds of flights and routes is inaccurate. Therefore, we compare only routes that are served by both, LCCs and TNCs. This is the subsample highlighted in Figure 1. Using the subsample does at least provide some basis for comparability. However, it might be that one carrier type is more present on longer routes relative to the other carrier type. To avoid bias by that we divide the average scheduled travel time by the average distance travelled (average scheduled travel time / km).

Hypothesis 3

Hypothesis 3 states *"even after controlling for airport size, competition and other factors, LCCs still register shorter arrival delays."*This calls for the first formal regression analysis of our study (see chapter 6.2). We want to find out about the difference in arrival delay between LCCs and TNCs – under the condition that everything else is equal. The regression will be based on the equation below which represents the assumed relationship between arrival delay and its explaining factors. All factors refer to the literature review from chapter 2.2. Precisely, we consider arrival delay as a function of mainly eighteen factors. However, we might decide at a later stage to drop some variables due to strong correlation.

$$delay\_min\_a_{it} = f(SlotCoordinationLevel_o, SlotCoordinationLevel_d, AirportHubSize_o, AirportHubSize_d, AirlineHubSize_o, AirlineHubSize_d, RouteCompetition_r, HHI_o, HHI_d, NormalizedDepartureTime_{jt}, FlightDistance_i, SeatingCapacity_{it}, DayOfWeek_{it}, Month_{ij}, AdverseWeather_o, AdverseWeather_d, ExceptionalEvents_{od}, LCC_i) \tag{1}$$

The index (*it*) of the *delay_min_a* variable in equation (1) reflects that we will exploit the high level of accuracy that our data set allows us to investigate. This means that we run our estimations on individual flight level. Equation (1) describes the arrival delay of a particular flight *i* at a particular time *t* (day and time of day). Flight *i* thereby specifies a combination of an operating airline *j* and a route *r* that connects origin *o* and destination *d.* Using flight level data allows us to explicitly control for flight-specific factors that influence arrival delays, such as departure time or adverse weather on a particular day.

The main independent variable of interest is the measure of carrier type. In our equation we include a dummy variable (LCC_i) to mark whether the flight is a LCC or TNC flight. This variable then captures the average difference in arrival delay between TNCs and LCCs, while comparing them under similar circumstances.

Hypothesis 4

Independent of whether we find indication that some airlines engage in more schedule padding than others or not (hypothesis 3), we will investigate a measure of OTP that is unaffected by airline's scheduling decisions. We consider excess travel time as more "objective". Chapter 2.1 introduced excess travel time which we adopt in our analysis:

Hypothesis 4 ("*After controlling for airport size, competition and other factors, LCCs register shorter excess travel time")* requires a similar statistical approach as hypothesis 2. We will use a regression, too. For simplicity reasons we will also use exactly the same control variables (see chapter 6.2). A LCC dummy variable is included as main independent variable and allows for comparison with the coefficient of the arrival delay regression.

Hypothesis 5

We go a step beyond the *overall* LCC effect. Instead we compare means across individual airlines thereby observing individual airline-specific effects. Thereby, we are able to refer to hypothesis 5 that stated: *the overall LCC OTP is driven by a homogenous set of individual OTP*. Precisely, airline-specific dummy variables will reveal whether individual airlines' performances are in line with the overall performance of the group (LCC vs. TNC) they belong to. We compare size and magnitudes of individual airlines effects with the overall LCC effect. Given that individual airlines' shares in the sample will not be fully constant, we will also be able to comment on to what extent the overall LCC effect is severely driven by an exceptional performance of a dominant airline in the sample. Thereby, we add transparency to the existing research. The analysis of individual airlines stretches throughout the entire research (see chapter 6.1 and 6.2). In the regression analysis we will include individual airline-specific dummy variables as main independent variables of interest.

Control Variables

We use mainly different types of control variables. Generally, we divide them into five broad categories: Airport variables, economic/competitive variables, logistical variables, weather variables and other variables. Most control variables are listed in Table 3. Not listed but included are fixed-effect dummies for each month[13]. An extended table that includes all mean values is included in Appendix C.

We want to highlight the distinct features that many of our control variables share. There are basically two such features: their time invariance and categorical nature. All airport variables and economic/competitive variables are time invariant. Due to restrictions in data collection we can only document these variables once. This issue will be further elaborated on later in this chapter. At that point we will also explain how (and why) we used a dedicated data set to construct these variables. As mentioned, many of our control variables are categorical variables based on quantitative data. With the help of that we are able to account for the expected nonlinearity in the relationship between some variables and OTP.

Some control variables, such as slot coordination, hub categories, and airport concentration, require some further explanation. In fact, the three levels of slot coordination are based on the IATA's Worldwide Scheduling Guidelines (IATA, 2010). The four hub size categories, on the other hand, are not based on any international standard but aligned with other academic research, which supports comparability. For the HHI holds that an index value close to zero implies the existence of many airlines that all have quite a small market share at an airport. An index value of one, as opposed to that, shows that there is only one carrier dominating the airport. In addition, Appendix D contains a short section about how the HHI index has been constructed.

[13] Time fixed effects also to prevent spurious results.

Category		Variable	Unit	Definition
Airport	Slot Coordination	*lev1_d*	0;1 ▲	whether the departure airport is non-coordinated
		lev2_d	0;1 ▲	whether the departure airport is schedule facilitated
		lev3_d	0;1 ▲	whether the departure airport is coordinated
		lev1_a	0;1 ▲	whether the arrival airport is non-coordinated
		lev2_a	0;1 ▲	whether the arrival airport is schedule facilitated
		lev3_a	0;1 ▲	whether the arrival airport is coordinated
	Airport Hubs	*nhub_ d*	0;1 ▲	whether the observed flight departs from a non-hub airport (number of destination ≤ 25)
		shub_d	0;1 ▲	whether the observed flight departs from a small hub airport (25 > number of destinations ≤ 45)
		mhub_d	0;1 ▲	whether the observed flight departs from a medium hub airport (45 > number of destinations ≤ 70)
		lhub_d	0;1 ▲	whether the observed flight departs from a large hub airport (number of destinations > 70)
		nhub_a	0;1 ▲	whether the observed flight arrives at a non-hub airport (number of destination ≤ 25)
		shub_a	0;1 ▲	whether the observed flight arrives at a small hub airport (25 > number of destinations ≤ 45)
		mhub_a	0;1 ▲	whether the observed flight arrives at a medium hub airport (45 > number of destinations ≤ 70)
		lhub_a	0;1 ▲	whether the observed flight arrives at a large hub airport (number of destinations > 70)
	Airline Hubs	*airl_nhub_d*	0;1 ▲	whether the observed flight departs from a non-hub airport (number of destination ≤ 25)
		airl_shub_d	0;1 ▲	whether the observed flight departs from one of its own small hub airport (25 > number of destinations ≤ 45)
		airl_mhub_d	0;1 ▲	whether the observed flight departs from one of its own medium hub airport (45 > number of destinations ≤ 70)
		airl_lhub_d	0;1 ▲	whether the observed flight departs from one of its own large hub airport (number of destinations > 70)
		airl_nhub_a	0;1 ▲	whether the observed flight arrives at a non-hub airport (number of destination ≤ 25)
		airl_shub_a	0;1 ▲	whether the observed flight arrives at one of its own small hub airport (25 > number of destinations ≤ 45)
		airl_mhub_a	0;1 ▲	whether the observed flight arrives at one of its own medium hub airport (45 > number of destinations ≤ 70)
		airl_lhub_a	0;1 ▲	whether the observed flight arrives at one of its own large hub airport (number of destinations > 70)
Economic/ Competitive	Route Compet.	*mon*	0;1 ▲	whether the observed flight operates on a monopoly route (served by just one carrier)
		Duo	0;1 ▲	whether the observed flight operates on a duopoly route (served by two carriers)
		>2comp	0;1 ▲	whether the observed flight operates on a competitive route (served by more two carriers)
	HHI	*hhi_d*	[0,1] ►	Herfindahl-Hirschmann-Index at departure
		hhi_d	[0,1] ►	Herfindahl-Hirschmann-Index at arrival

Logistical		*normdept*	[0,1] ►	Normalized departure time (00:00 equal 0; 23:59 equals 1)
		Dist	km►	approximate flight distance between arrival and departure airport
		seatcap	►	approximate number of seats available based on airplane type (individual airline-specific adjustments are not accounted for)
	Days of Week	*mon*	0;1 ▲	whether observed flight takes place on Monday
		Tue	0;1 ▲	whether observed flight takes place on Tuesday
		wed	0;1 ▲	whether observed flight takes place on Wednesday
		Thu	0;1 ▲	whether observed flight takes place on Thursday
		Fri	0;1 ▲	whether observed flight takes place on Friday
		Sat	0;1 ▲	whether observed flight takes place on Saturday
		Sun	0;1 ▲	whether observed flight takes place on Sunday
Wea-ther		*advweath_d*	0;1 ▲	whether the departure airport is affected by adverse weather on the observed day
		advweath_a	0;1 ▲	whether the arrival airport is affected by adverse weather on the observed day
Other		*strike_da*	0;1 ▲	whether the departure and/or arrival airport is affected by strike on the observed day
		Lcc	**0;1 ▲**	**whether observation is a LCC flight (main independent variable)**

▲ Dummy variable
► Continuous or discrete variable

Table 3: Variable Definition

Construction of Control Variables

Our control variables are only partly constructed from the data set mentioned in section 5.1. Some of them rely on other data sources. From the OAG data set we obtain our dependent variables as well as individual airline-specific dummies and time related variables (e.g. departure time, day of week and month).

Nonetheless, it is hard to assess the level competition on routes, concentration at airports and hub size since our OAG data set only covers intra-European destinations and a limited number of airlines. The data set reflects competition between the major European carriers while it ignores, for instance, smaller carriers that are, in fact, strong competitors on a distinct geographical scope, but not large enough in total to be included in our analysis.

A less-than-ideal approach helps to construct some of the competitive variables. Thanks to OAG we have access to another data set that was provided as one piece. That data set covers schedule data of all worldwide flights operated between 5th March and 12th March 2012. In the following we will refer to that data set by using the term “March data set”. With help of that we are able to specify some of our control variables. We find answers to the following questions related to our control variables: how many destinations does an airline serve from a given airport? To what extent have particular airlines dominant positions at airports? Which routes are monopolistic / duopolistic?

However, the approach has some drawbacks to be kept in mind. First, assessment of variables is solely based on that single week in March. The insights from that week are used for the whole period of observation. That is why some variables are time invariant. We assume that over the sample period of six months there are no large-scale changes in airline schedules. Accordingly, we do not expect airport concentration, route competition and hub size to vary dramatically during our sample period. Also on the short-term, i.e. between weekdays and weekends for instance, we assume no changes. Other scholars are stricter about that. Rupp accounts for potential day-to-day changes by calculating concentration on daily level. Others update concentration every month, which is useful considering that during the long sample periods of five to ten years circumstances may change.

For seating capacity and slot coordination we use extra sources. Our main OAG data set specifies the employed aircraft type for each flight, so that we can easily enrich our dataset by data on seating capacity[14]. The individual airlines' exact seating capacity may differ from the maximum seating capacity we included in our data set. But at least it is a useful approximation. Furthermore, the level of slot coordination at each airport can be found in the IATA's Worldwide Scheduling Guidelines (IATA, 2010). From OpenFlights[15] we obtain linear distances in km between each origin destination pair.

Unfortunately, we are not able to accurately control for adverse meteorological conditions. Difficulties in data collection are the main reason. In principal, the large majority of European airports are active weather reporting stations which collect data on frequent basis. However, complete European data is not easily accessible to the public as it is in the U.S. via the tools of the National Oceanic & Atmospheric Administration (NOAA). There is no such tool on European level. Instead we may use national weather services and private weather services that offer data, such as historical observations on

[14] Seating capacity of aircraft types is obtained from aircraft manufacturers' websites and aircraft databases on the internet. This is only an approximation. Typically, airlines are free to configure airplanes according to their preferences. Some airlines, for instance, go without space-sapping business class and therefore are able to install more seats.

[15] www.openflights.org

daily and hourly basis. However, we will not make use of these sources because of several reasons[16].

Not considering weather at all would harm our analysis. In chapter 2.2 we learned that weather is a major root cause of flight delays. In fact, we want to investigate the difference in OTP of LCCs and TNCs, so we cannot ignore that some carriers probably serves a higher share of "difficult" airports with respect to weather than the others do. The "ATFCM Weekly Briefings" lists adverse weather per day and airport[17], which allows us to create a weather control variable.

[16] This data is not perfectly suitable for this research due to four reasons: (1) While we can easily access data on temperature and precipitation, we struggle to find data on other weather conditions affecting air traffic (e.g. cumulonimbus or low ceiling) (2) access to data is partly charged (3) historical weather data does only involve certain stations which leads to missing data in the sample (or approximations by using the closest available station). (3) Only small amounts of data can be retrieved at a time which is too time-consuming considering the large sample size.

[17] To illustrate the level of precision in the weather reporting, we cite EUROCONTROL's March report. There it says for the March 3rd: "EDDM fog. LSZH low visibility. […]".It should be kept in mind that the actual level of delays does not only depend on the actual weather conditions but also on how authorities deal with it and what short-term regulations they put in place.

6 Findings

6.1 Sample Characteristics

In this chapter we want to get familiar with the composition of our sample. The section sheds light on the sample's basic characteristics. We will also confirm the fundamental difference in airport usage between LCCs and TNCs, which is suspected to have an influence on OTP.

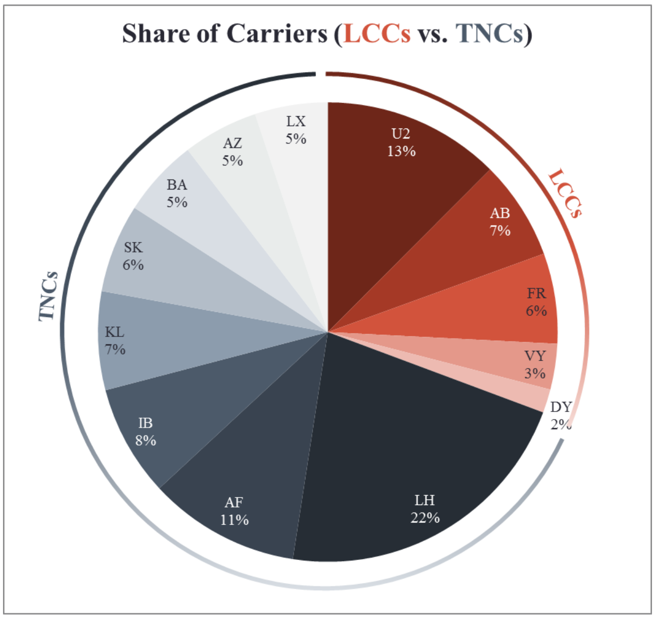


Figure 2: Share of Carriers (LCCs vs. TNCs)

Figure 2 depicts individual proportions of each single carrier. It shows that LCCs make up around on third of the whole sample. Among them, easyJet constitutes the largest carrier (ca. 13%). Lufthansa contributes around 22% of all observation. With this large share, Lufthansa is not only the most observed TNC but also the most observed airline in general within the sample. However, it should be noted that these shares do not reflect actual market shares[18].

Observations are almost equally distributed over the sample period. Accordingly, each month comprises around one sixth of total observations. Moving from months to weeks as units of observation, we note that from Sunday to Thursday daily traffic comprises around one seventh of total observations (ca. 14%). On Saturdays, however, traffic is

[18] There are two main reasons: first, proportions are exclusively related to the sample of 13 airlines; second, we deleted records that missed data or where not plausible with respect to their documented arrival/departure time information. Thus, carriers' shares are only to a limited extent representative. To be more precise about representativeness, we compare our sample distribution with the carrier distribution of the March data set. The respective data set contains all intra-European flights from various airlines during a single week in March 2012. What we infer about representativeness is only an approximation. Comparing the two samples, we see that our 13 airlines can be assigned to around one half of all operated flights. The remaining 50% of the observations from the March data set belong to various other airlines. In fact, there are far more than 100 other airlines operating within Europe. The shares within our group of 13 airlines are relatively well portrayed. Only 4 airlines are either slightly under-sampled (FR, SK) or slightly over-sampled (LH, IB).

much lower (12%). By contrast, Thursdays and Fridays are relatively traffic-intense (ca. 15%).

With respect to adverse weather it should be noted that 7% of our observations are affected by adverse weather at departure and again 7% by adverse weather at arrival. Not even 1% of all flights suffer from both, adverse weather at departure and arrival. Certainly, these values underestimate the real occurrence of (severe) adverse weather conditions that have an impact on take-off and landing. The top four airports (areas) affected by adverse weather are London, Frankfurt, Munich and Amsterdam.

Compared to adverse weather, the occurrence of strikes is relatively rare. Less than 0.5% of all observed flights operate on days where their departure and/or arrival airport is affected by strike or where the airline crew itself is on strike. In fact, Lufthansa's German hubs have a comparatively high strike rate during our sample period, which is due to a broad Lufthansa crew strike in summer 2012. Therefore, it is not surprising that Lufthansa is the most strike-affected airline within our sample.

The usage of airport hubs varies across carrier types and individual carriers. An investigation of the whole sample reveals that "large hub-large hub" flights comprise around 42%. Such connections are not entirely covered by TNCs – in fact, around one quarter is comprised by LCCs. Considering each carrier type's share in the sample we see that TNCs and LCCs make similar use of such connections. Around 90% of all flights do either depart from or arrive at large hubs. As opposed to that, there are only a few "non-hub-non-hub" pairs. Not even 0.5% of the whole sample can be attributed to that category. Cases where either the departure or the arrival airport is a non-hub make up around 17% of the sample. Again such flights are served by both carrier types.

Figure 3 illustrates each carrier's individual usage of airport hubs at departure. It reveals that usage of airport hubs in our sample varies across individual carriers. There are four main findings. First, large hubs (more than 70 destinations) are very dominant as we mentioned already. Second, British Airlines and KLM make intensive use of large hubs. Third, Ryanair has the lowest share of large hub departures. Fourth, Vueling is somehow exceptional – all other LCCs have much lower shares of large hub departures than TNCs have. In fact, Vueling departs from large hubs roughly as often as the TNC KLM, which may be explained by the fact that it predominantly flies from Barcelona.

We add to these findings about airport size that there is also a large difference with respect to route competition. While around 20% of all TNC flights operate on monopolistic routes, LCCs hold a monopolistic position in almost 45% of all cases.

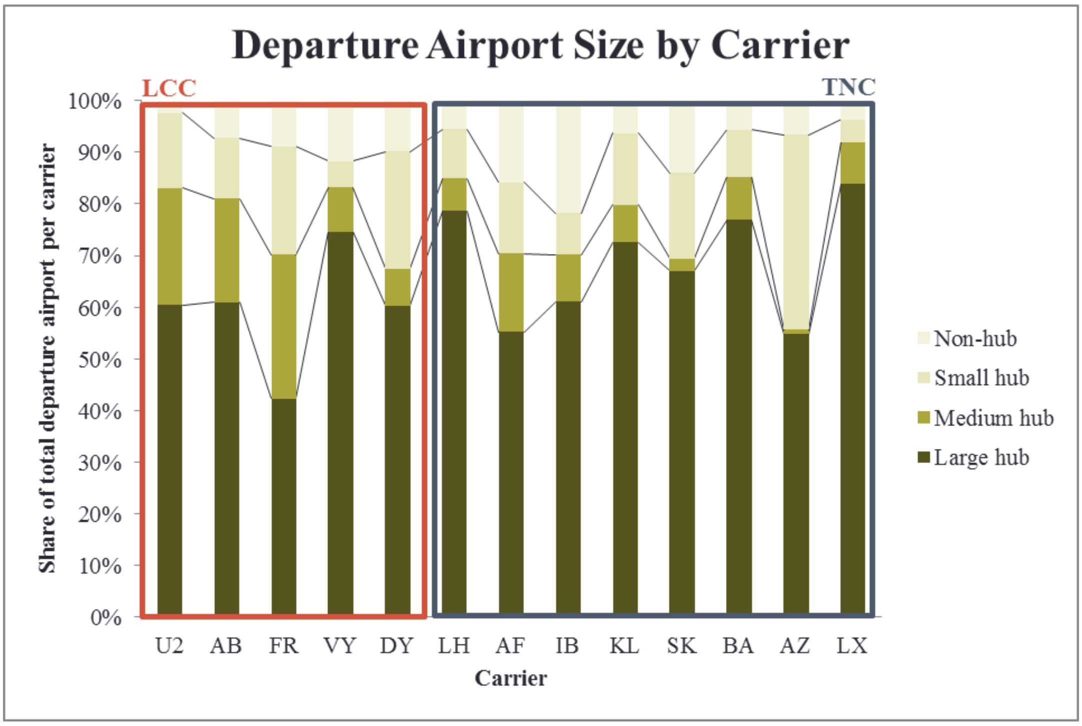


Figure 3: Departure Airport Size by Carrier

6.2 Basic Two-Mean Comparison

This section focuses on hypothesis 1 and 2 that both call for a two-mean comparison in arrival delay between LCCs and TNCs. Before that we will take a broad look on OTP, also checking departure delay. Later on we limit our investigation to arrival delay.

Figure 4 graphically illustrates the proportions of on-time, delayed and over-punctual flights by carrier type at arrival and departure. The numbers show that almost 60% of LCCs flights in our sample departed behind schedule. TNCs have fewer delayed departures – only around 54% departed delayed. However, it is interesting that LCCs seem to “catch up” during flight operations. At arrival LCCs perform much better: only 31% of LCCs’ flights arrive behind schedule, whereas 45% of TNCs’ flights are delayed. With this first findings for Europe we find similar evidence as Rupp & Sayanak (2008) found for the U.S. The difference between OTP at departure and arrival suggests that LCCs (1) either experience less air traffic congestion than non-LCC carriers and/or (2) allocate more time to serve a route than non-LCCs.

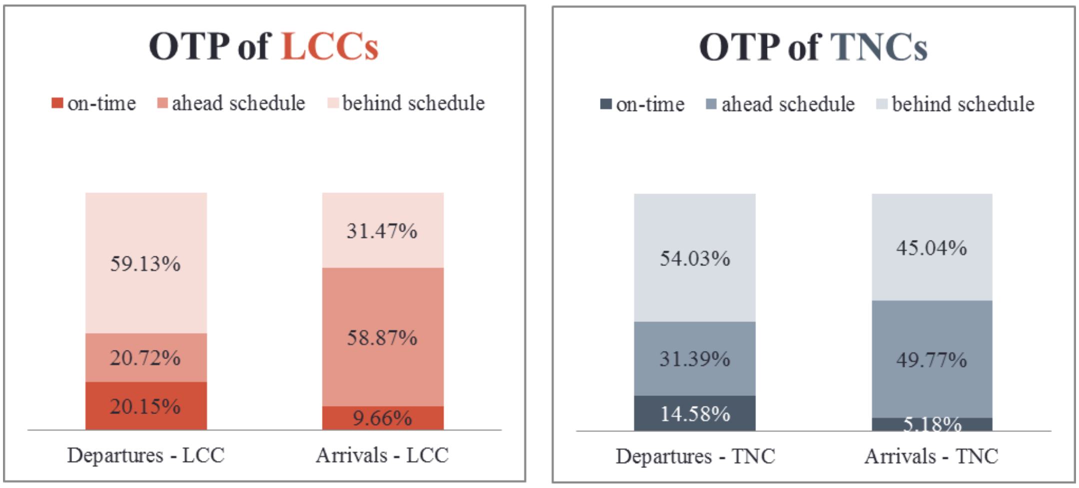


Figure 4: OTP of LCCs and TNCs

Table 4 adds detail to the insight from Figure 4. It shows mean values by grouped carrier type as well as individual carriers. Highlighted in green and grey are the best and worst performers for each variable. As observed before, at departure TNCs largely perform better than LCCs. Best performers at departure are depending on the variable KLM, SAS and Alitalia. KLM, for instance, has the lowest share of departures with a delay of one minute and more (40.44%). However, at arrival LCCs achieve better OTP. While best performers are only LCCs, worst performers can solely be found among the TNCs. EasyJet has the lowest share of delayed arrivals (*del>=1_01_a*) in the entire sample (23.13%). Second and third best performers in this category are the LCCs Norwegian (25.59%) and Ryanair (27.68%).

We learnt that easyJet has the lowest share of arrivals that are delayed by one minute or more (*del>=1_01_a*). However, we asked ourselves: how does the rank of easyJet change if we adopt the DOT's and Flightstat's 15 minutes allowance for the definition of delays? This allowance is very common and most rankings are based on it. In Appendix D we show that changes in the ranking largely occur at easyJet's charge. We also conclude from that: TNCs have comparatively many short delays. These delays become "invisible" if we adopt the 15 minutes allowance. As a result TNCs perform better under this evaluation method.

Two-Mean Comparison Results – Overall LCC effect in Arrival Delay (Hypothesis 1)

Most importantly, LCCs' average arrival delay in min (*delay_min_a*) is around one minute smaller than the one of TNCs. On average, LCCs arrive 5.82 minutes late, whereas TNCs mean arrival delay is 6.88 minutes. Like for all other variables in Table 4, t-tests revealed that this difference is significant. This finding allows us to confirm hypothesis 1. We conclude: given LCCs' airport, route and scheduling choices, LCCs have shorter arrival delays than TNCs.

Having a look at other OTP measures reveals how this difference evolves. In fact, LCCs have a lower share of delayed arrivals than TNCs (31.47% vs. 45.04%). At the same time, if delayed, LCCs have a larger average arrival delay than TNCs (18.47 min vs. 15.27 min). Thus, the higher average arrival delay of all delayed LCCs flights gets wiped out by the smaller proportion of flights being delayed.

	Variable								
	Departure				Arrival				Excess
Airline or carrier type[1]	Avg. deviation from schedule at departure in min (*scheddev_min_d*)[3]	departure delay in min (*delay_min_d*)[5]	% of at least one minute delayed departures (*del>=1_01_d*)	avg. departure delay in min, if *del>=_01_d* = 1	Avg. deviation from schedule at arrvial in min (*scheddev_min_a*)[4]	arrival delay in min (*delay_min_a*)[6]	% of at least one minute delayed arrivals (*del>=1_01_a*)	avg. arrival delay in min if *del>=1_01_a* = 1	avg. Excess travel time in min (*excess_min*)
U2	10.55	11.47	59.18%	19.38	-4.61	4.95	23.13%	21.39	29.41
AB	6.86	8.48	49.83%	17.02	4.55	8.40	48.42%	17.34	26.92
FR	10.08	10.85	66.30%	16.36	-2.39	4.78	27.68%	17.26	29.24
VY	9.81	10.73	66.92%	16.04	2.40	7.00	37.61%	18.62	36.09
DY	6.64	7.89	55.33%	14.27	-4.08	3.23	25.59%	12.63	23.52
LCCs[2]	9.32	10.39	59.13%	17.57	-1.31	5.82	31.47%	18.49	29.19
LH	6.89	7.89	61.21%	12.89	3.62	7.17	49.28%	14.54	23.66
AF	5.00	6.35	52.17%	12.18	1.08	5.40	40.88%	13.22	23.43
IB	6.02	7.50	53.36%	14.06	6.56	9.87	56.90%	17.35	29.48
KL	3.21	5.25	40.44%	12.99	-1.98	4.06	30.98%	13.10	22.94
SK	2.38	4.23	42.54%	9.96	-0.80	3.90	33.54%	11.62	18.70
BA	8.90	10.42	47.49%	21.97	7.05	10.97	52.33%	20.98	30.55
AZ	7.96	8.64	54.45%	15.87	1.32	5.74	35.66%	16.09	33.53
LX	8.93	9.87	67.60%	14.61	5.18	8.46	52.75%	16.04	25.46
TNCs[2]	6.11	7.42	54.03%	13.73	2.81	6.88	45.04%	15.27	25.19
Overall	7.10	8.33	55.59%	14.98	1.55	6.55	40.88%	16.03	26.42

[1] Recall airline's codes: easyJet (U2), Air Berlin (AB), Ryanair (FR), Norwegian (DY), Vueling (VY), Lufthansa (LH), Air France (AF), Iberia (IB), KLM (KL), SAS (SK), British Airways (BA), Alitalia (AZ), Swiss (LX)

[2]Weighted average. To verify the difference in means across carrier types (LCCs vs. TNCs) we consult t statistics. T statistics are sufficiently large to reject the null hypothesis of no mean difference between LCCs and TNCs.

[3] Departure schedule deviation: max. 255 minutes; min. -59 minutes

[4] Arrival schedule deviation: max. 343 minutes; min. -140 minutes

[5] Departure delay: max. 255 minutes; min. 0 minutes

[6] Arrival delay: max. 343 minutes; min. 0 minutes

Table 4: Two-Mean Comparison OTP

Two-Mean Comparison Results – Difference in Scheduled Travel Time (Hypothesis 2)
We already found out that LCCs seem to catch up during flight operation and alleged schedule padding. For more insights about schedule padding we will now compare LCCs' and TNCs' scheduled flight times based on a subsample of overlapping routes[19]. We observe that LCC flights take on average 101.39 minutes, while TNCs require only 90.54 minutes on average. The t-test confirms that there is a significant difference of almost 11 minutes scheduled flight time.

However, if we correct for average flight distance the difference vanishes. On the overlapping routes, LCCs schedule on average 0.123 minutes per km, whereas TNCs schedule 0.127 per km[20]. The t-test reveals that the difference is insignificant. Based on that, we reject hypothesis 2. To conclude: there is no significant difference in scheduled travel time between LCCs and TNCs. Therefore, we found no indication that one carrier type tends to include more buffer time than the other.

6.3 Regression Analysis

We will now further isolate the overall LCC effect and individual airline-specific effects. We will be using regression analyses that control for the influence of other factors that affect OTP. The regressions comply with the proposed statistical methods for hypothesis 3, 4 and 5 (see Figure 1). The dependent variables are *delay_min_a* and *excess_min*.

This chapter is structured as follows: first, it presents a short correlation analysis that gives a tentative idea about the relationship of arrival delay and its potentially explaining factors. Second, it will comment on the selection of proper regression models. Thirdly, the chapter reports on the regression results, going through the results hypothesis by hypothesis.

Correlation Analysis
We note that OTP measures are not too strongly correlated with our independent variables. Correlation coefficients exceed |0.1| only in just a few cases. The correlation matrix in Appendix F also reveals that the variable *delay_min_a* is most correlated with adverse weather conditions at arrival and departure (*adverse_d* and *adverse_a*) and the normalized departure time (*normdep*). In these cases, the coefficients are positive,

[19] n = 334,870 individual flights.
[20] Average flight distance on overlapping routes: LCC = 826.15 km; TNC = 714.02 km.

meaning that flights tend to have larger delays at arrival when there are adverse weather conditions or departure time is late. Less strong but also positive is the dummy for fully coordinated airports (*lev1_a*), implicitly confirming the assumption that more congested airports have higher average arrival delays. Next to that we find that operation on monopoly routes (*mono*) tends to reduce arrival delays.

In that context, we recall that LCCs operate on monopolistic routes more frequently than TNCs. Even though the correlation between these factors and arrival delay is not too strong, we are curious to what extent the strong performance of LCCs (see hypothesis 1) is driven by such route choices, for instance. Our regressions will help to adjust the overall LCC effect from hypothesis 1.

Regression model selection

At first we choose the appropriate regression models. The selection of the model largely depends on distributional characteristics of the dependent variable. *Delay_min_a* and *excess_min* are classified as count data. They share the three common properties of count data[21]: first, they do not take negative values; second, they take integer values; and third, they are positively skewed as the histograms in Appendix G illustrate.

Count data rules out OLS regression, which would be a natural starting point. OLS is problematic because it assumes residual errors to be normally distributed. In some cases (e.g. a skewed continuous variable) a (log-) transformation helps to produce errors that approximately follow a normal distribution. However, in our case the high number of zero observations (e.i. zero minutes delay) complicates the transformation from a skewed distribution to a normal distribution[22]. Moreover, OLS could practically also predict negative values. This is theoretically impossible if we recall our delay definition.

As a consequence, our data calls for dedicated count data models. Most widely used is the Poisson model or the negative binominal model (NB). Both models are expected to fit our data better than OLS, because they are based on a skewed, discrete probability distribution and permit estimated values to be negative.

[21] To clarify these features, recall that *delay_min_a* does not equal schedule deviation. In line with the definition from section 2.2 flights that are on-time or too early have a delay of 0 minutes. Also excess travel time (*excess_min*) can only be non-negative by definition – a particular flight can never perform better than the same month's best-performer but only just as good. Accordingly, we denote these two variables by "y,y ∈ " N_0= {0,1,2,…}.

[22] The logarithm of zero is not defined.

We prefer the NB model over the Poisson model because our two variables violate an important pre-condition of the Poisson model. The Poisson model assumes that the expected value is equal to the variance. This feature of the Poisson model is widely known as equi-dispersion property. As said, our variables violate this property. De facto, their variances exceed the means by far. Depending on which variable we observe, the variance is 12 times or even 36 times than the mean[23]. An extra formal test according to Cameron & Trivedi (2010) confirmed this complication: our data is so-called "over-dispersed". Accordingly, we favour the NB model. We verify that NB models are superior to Poisson models by investigating goodness-of-fit statistics of our regressions[24].

The *delay_min_a* regression clearly requires a subclass of the NB model, the so called zero-inflated negative binomial model (ZINB). As the model's name implies the ZINB model accounts for excess zeros in the dependent variable. We note that *delay_min_a* shows a large excess of zero observations. At arrival more than half of our total observations show zero minutes delay (59.12%). The Vuong test confirms the appropriateness of the ZINB model at 1% significance level.

Excess_min does not show such an inflation of zeros, so that the usage of the ZINB model is not self-evident. In fact, not even 2% are zero observations[25]. However, we carefully check goodness-of-fit statistics to decide whether the ZINB model may also be appropriate here. We find that – for counts above zero – the NB and the ZINB model both predict probabilities that are close to actual frequencies. For zero excess travel time, however, the NB model seriously underestimates actual frequencies compared to the ZINB model. We consult the Vuong test again and find that it also favours the ZINB model at a 1% significance level for *excess_min*. Thus, we will proceed with the ZINB model in all our regressions.

[23] Precisely, the variance of *delay_min_a* (239.01) is far higher than its mean (6.55). Comparatively, *excess_min* shows a variance (213.23) is around 12 times larger than its mean (18.09).
[24] The R^2 that we know from linear models is not applicable in this case. Instead, we use a few other statistics: (1) the user-written STATA "countfit" command (2) log-likelihood values (3) AIC/BIC statistics. Moreover, every NB regression contains statistics of the over-dispersion parameter α. If α is not significantly different from zero the NB distribution is equal to a Poisson distribution. At this point, we can already tell that in the models that we will present later α is always significantly different from zero. Therefore, we have another formal proof that NB models are appropriate.
[25] Recall that zero observations in case of *excess_min* represent the best performing benchmark flights that other flights are compared to. These flights operated within the minimum feasible travel time.

A major strength of the ZINB model is that it allows us to differentiate between the probability of a flight being delayed and – in case of delay – the actual size of the delay in minutes. Accordingly, the ZINB regressions contain two parts. The first part estimates the probability P of being on-time as a function of our independent variables, using a logistic function. The second part – a negative binomial equation – then predicts the expected delay size in minutes. The excess travel time ZINB regressions follow the same logic.

The on-time probability as well as the delay size is modelled as functions of the same independent variables. Notwithstanding; we do not include all control variables that equation (1) suggested. We drop the airport hub size effect due to correlation with the slot coordination variables[26].

The full results of our ZINB estimations are included in Table 5. The delay regressions (*delay_min_a*) occur in the left part of the table, whereas the excess travel time regression (*excess_min*) is shown on the right side. For both, we distinguish between a basic model that is concerned with the overall LCC effect and a modified model that contains individual airline-specific effects .

The logistic estimations always occur at the top, further down on the second page of the output the negative binomial estimation is presented. Consider that the logistic estimates reflect the probability P of being on-time. Positive logistic coefficients increase the probability of being on-time. In order to get an idea *how much* things are changing, we first calculate odds ratios and then the percentage change in odds.

Regression Results - Overall LCC Effect in Arrival Delay (Hypothesis 3)

Hypothesis 3 asks for the difference in arrival delay between LCCs and TNCs – under the condition that everything else is equal. To give answer to that we consult the regression output in column 2, 3 and 4 of Table 5.

We find that for most independent variables our arrival delay regression results are largely as expected. More than 70% of our independent variables are significant predictors of arrival delay. Many of the independent variables seem to affect the probability of being on-time as well as in case of delay the exact size of the delay.

---

[26] Based on an extended correlation analyses we observed that the level of slot coordination as well as airport hub size highly reflect airport size and congestion. We double-check our decision to drop airport hub size variables by investigating goodness-of-fit statistics with and without these variables. In fact, including airport hub variables does not decrease the AIC or BIC statistics.

Among these variables are also the two coefficients of our main independent variable, the LCC dummy variable.

LCC flights are more likely to be on-time than TNC flights. This still holds under the "everything else equal assumption" which is valid for all the following regressions. Given that, we note that operation by LCCs increases the probability of on-time arrival – even if we subtract out the favouring effect of monopoly routes and non-congested airports. To be precise, LCC flights' odds[27] of being on-time are around 120% higher than TNC flights'. What we cannot do is to quantify the exact difference in on-time arrival probabilities because these probabilities depend on what values the other variables take[28].

The negative binominal section complicates a clear inference with respect to hypothesis 3. It reveals that in case of delay the expected size of the delay in minutes tends to be higher for LCCs than for TNCs. In case of delay, the expected delay for a LCC flight is 27% higher than the expected delay of a TNC flight that operates under exactly the same circumstances. To sum up: the probability of being delayed is lower of LCCs; but – in relatively rare case of delay then – LCCs are expected to have higher delays than TNCs.

These results do not allow either confirming or rejecting hypothesis 3. Instead, the ZINB model is only able evaluate two separated, more differentiated hypotheses:

> **Hypothesis 3a:** *Even after controlling for airport size, competition and other factors, LCC's probability of being on-time is still higher than for TNCs.*
> **Hypothesis 3b:** *(Even) after controlling for airport size, competition and other factors, LCCs (still) register shorter arrival delays in case of delay*[29].

Our results confirm hypothesis 3a, but reject hypothesis 3b. In fact, this is in line with our introductory findings in the "basic two-mean comparison" section.

Regression Results – Overall LCC Effect in Excess Travel Time (Hypothesis 4)

[27] Odds of being on-time = probability of being on-time / probability of being delayed

[28] As opposed to that odds ratios are constant. They are independent of what values the other dependent variables take. We can calculate exact probabilities once we define specific values for each of the independent variables.

[29] We put "even" and "still" in brackets because we found in chapter 6.2 that LCCs actually have higher arrival delays in case of delay.

In the first instance, we have no reason to be sceptical about the findings right above. We assume that the arrival delay regression results are not biased by schedule padding. This assumption is based on chapter 6.2, which indicated that neither one of the two carrier types tends to include more buffer time.

However, the statistical method we used to reject hypothesis 2 was not very sophisticated, which makes us switch to excess travel time as dependent variables in this section. The results of the related ZINB model with *excess_min* as dependent variable are presented in Table 5, too. There we find that most control variables do also play a significant role in explaining excess travel time.

Using excess travel time as OTP measurement, changes our results in favour of LCCs. Again, LCCs perform better in the logistic estimation, meaning that everything else equal, LCC flights are more likely to achieve a route's (and month's) minimum feasible travel time. LCC flights' odds of being on-time are much higher than TNC flights' (ca. 163% as opposed to 120% in the arrival delay regression). At the same time, we cannot confirm the arrival delay regression's conclusion about the inferiority of LCCs when it comes to expected size of delays in minutes. It is rather that the carrier type does not significantly influence the size of excess travel time at all. The coefficient is very small. If there is a difference at all, the expected excess travel time of LCCs is not even 2% smaller compared to TNCs' expected excess travel time.

We conclude that LCC flights are more likely to operate within the minimum feasible travel time. If they do not, their minutes delay compared to the minimum feasible time is not significantly different from TNCs' delay. If we now join these findings, we are able to confirm hypothesis 4:

> **Hypothesis 4:** *After controlling for airport size, competition and other factors, LCCs register (on average) shorter excess travel time.*

Obviously, under regular OTP measurements (*delay_min_a*) LCCs are comparatively discriminated. The more objective OTP measurement (*excess_min*) reveals that LCCs perform better than TNCs.

	Zero-inflated negative binomial regression model (ZINB) on arrival delays (*delay_min_a*) Obs = 1,056,842 (zero obs = 624,825)						Zero-inflated negative binomial regression model (ZINB) on excess travel time (*excess_min*) Obs = 1,056,842 (zero obs = 19,054)					
	Overall LCC effect			Individual airline-specific effects			Overall LCC effect			Individual airline-specific effects		
Variable	Coeff.	S.E.	Coeff.(%)	Coeff.	S.E.	Coeff.(%)	Coeff.	S.E.	Coeff.(%)	Coeff.	S.E.	Coeff.(%)
	Probability P of having no delay as logistic function[30]						Probability P of having no excess travel time as logistic function					
lev1_d	.3474***	.0675	41.5	.2256***	.0614	25.3	.6472***	.0932	91.0	.6854***	.1026	98.5
lev2_d	.1296***	.0481	13.8	.1655***	.0425	18.0	.3257***	.1135	38.5	.3020***	.1107	35.3
lev1_a	.2204***	.0716	24.7	.1087*	.0591	11.5	.6172***	.1046	85.4	.6208***	.1117	86.6
lev2_a	.0861*	.0503	9.0	.1314***	.0418	14.0	.0525	.0587	5.4	.0579	.0592	6.0
airl_shub_d	-.0024	.0498	-.2	-.1497***	.0454	-13.9	-.0615	.1051	-6.0	-.0851	.1131	-8.2
airl_mhub_d	-.1407**	.0668	-13.1	-.3055***	.0553	-26.3	-.3112***	.0723	-26.7	-.4561***	.0862	-36.6
airl_lhub_d	.0144	.0594	1.5	-.1576**	.0627	-14.6	-.1476	.1157	-13.7	-.1568	.1034	-14.5
airl_shub_a	.0003	.0512	.0	-.1341***	.0457	-12.5	-.1095	.0910	-10.4	-.1425	.0982	-13.3
airl_mhub_a	.1166	.0565	12.4	-.0358	.0521	-3.5	-.4035***	.0820	-33.2	-.5046***	.0935	-39.6
airl_lhub_a	.5223***	.0529	68.6	.3481***	.0623	41.6	-.4808***	.0843	-38.2	-.5604***	.1144	-42.9
Mono	.1497**	.0599	16.2	.0281	.0458	2.8	.6321***	.0634	88.2	.6212***	.0613	86.1
Duo	.0859**	.0390	9.0	-.0278	.0342	-2.7	.2218***	.0773	24.8	.2336***	0748	26.3
Hhi_d	.0142	.1533	1.4	-.0588	.1429	-5.7	.0605	.1480	6.2	.0410	.1573	4.2
Hhi_a	.0071	.1396	.7	-.0808	.1197	-7.8	.1457	.1960	15.7	.1089	.2118	11.5
Normdept	-.3101***	.0449	-26.7	-.3566***	.0440	-30.0	.6041***	.0890	83.0	.5686***	.0867	76.6
Dist	-.0001**	.0000	.0	-.0001***	.0000	-0.0	.0009***	.0000	0.1	.0009***	.0000	0.1
Seatcap	-.0032***	.0002	-.3	-.0029***	.0003	-0.3	-.0023***	.0007	-0.2	-.0029***	.0007	-0.3
advweath_d	-.4480***	.0225	-36.1	-.4450***	.0205	-35.9	-.1462**	.0726	-13.6	-.1269*	.0652	-11.9
advweath_a	-.5028***	.0217	-39.5	-.4960***	.0203	-39.1	-.0405	.0659	-4.0	-.0404	.0602	-4.0
Strike_da	-.2293***	.0428	-20.5	-.2163***	.0434	-19.4	.4811***	.1580	61.8	.4807***	.1493	61.7
Lcc	.7902***	.0438	120.4				.9680***	.0632	163.3			
AB (Air Berlin)				-1.1852***	.0599	-69.4				-.1338	.0902	-12.5
FR(Ryanair)				-.2361***	.0587	-21.0				.1153	.1095	12.2
VY (Vueling)				-.6559***	.0853	-48.1				-.2474**	.1000	-21.9
DY (Norwegian)				-.1116	.0915	-10.6				-.0010	.1422	-0.1
LH (Lufthansa)				-1.420***	.0514	-75.8				-.8759***	.0942	-58.4
AF (Air France)				-1.2781***	.0706	-72.1				-1.4873***	.1352	-77.4
IB (Iberia)				-1.8640***	.0801	-84.5				-1.1168***	.1112	-67.3
KL (KLM)				-.8278***	.0821	-56.3				-.6370***	.2020	-47.1
SK (SAS)				-.6758***	.0599	-49.1				-1.1548***	.1483	-68.5
BA (British Airways)				-1.3626***	.0636	-74.4				-.9141***	.1189	-59-9
AZ (Alitalia)				-.6380***	.1096	-47.2				-.2284	.2094	-20.4
LX (Swiss)				-1.3929***	.0648	-75.2				-.9121***	.1293	-59.8
_cons	.4534***	.0819		1.9756***	.0892					-4.4720***	.1519	
Table continued on next page												

[30] Coeff. gives the log-odds of on-time arrival. Exp(coeff.) gives the odds ratio, e.i. the odds of LCCs to arrive on-time are 2.20 times (= exp(0.7902)) higher than TNCs. We receive coeff. (%) by calculation [Exp(coeff.)-1]*100. As mentioned above in the text before, from log-odds we can directly make inferences about probabilities: Increasing the log-odds of an on-time arrival means increasing the probability, and vice-versa decreasing the log-odds of an on-time arrival means decreasing the probability. Thus, as the sign of the log-odds ratio shows the direction of its relationship.

	Arrival delay size in minutes in case of delay as NB model						Excess travel time size in minutes in case of excess travel time as NB model					
lev1_d	-.1307 ***	.0302	-12.3	-.0527**	.0234	-5.1	-.1708***	.0384	-15.7	-.1275***	.0336	-12.0
lev2_d	-.0249	.0195	-2.5	-.0173	.0172	-1.7	-.1179***	.0260	-11.1	-.0716***	.0236	-6.9
lev1_a	-.1403***	.0328	-13.1	-.0702***	.0255	-6.8	-.1000**	.0480	-9.5	-.0629	.0391	-6.1
lev2_a	-.0441**	.0188	-4.3	-.0382**	.0160	-3.7	-.1924***	.0339	-17.5	-.1288***	.0297	-12.1
airl_shub_d	-.1444***	.0219	-13.4	-.0045	.0194	-0.5	.0872**	.0364	9.1	.1912***	.0343	21.1
airl_mhub_d	-.1572***	.0209	-14.5	-.0450**	.0190	-4.4	.0145	.0500	1.5	.1203***	.0389	12.8
airl_lhub_d	-.2121***	.0209	-19.1	-.0138	.0233	-1.4	-.1510***	.0375	-14.0	-.0594	.0367	-5.8
airl_shub_a	-.1209***	.0219	-11.4	.0149	.0198	1.5	.0406	.0353	4.1	.1504	.0309	16.2
airl_mhub_a	-.1486***	.0196	-13	-.0442**	.0192	-4.3	-.0791**	.0332	-7.6	.0617**	.0321	6.4
airl_lhub_a	-.1548***	.0209	-14.3	.0444*	.0237	4.5	-.0038	.0320	-0.4	.0889***	.0318	9.3
Mono	.0250	.0188	2.5	.0290*	.0172	2.9	-.1324***	.0400	-12.4	-.1718***	.0273	-15.8
Duo	-.0201	.0145	-2.0	.0041	.0126	0.4	-.0935***	.0266	-8.9	-.0850***	.0228	-8.1
Hhi_d	.0693	.0640	7.2	.0676	.0615	7.0	-.0624	.0975	-6.1	-.0833	.0887	-8.0
Hhi_a	.0133	.0582	1.3	.0311	.0528	3.2	-.2405***	.0900	-21.4	-.2740***	.0791	-24.0
Normdept	.6628***	.0221	94.0	.6406***	.0223	89.9	-.0969***	.0146	-9.2	-.1108***	.0140	-10.5
Dist	.0001***	.0000	0.0	.0001***	.0000	0.0	.0002***	.0000	0.0	.0003***	.0000	0.0
Seatcap	.0003**	.0001	0.0	-.0000	.0001	-0.0	.0010***	.0002	0.1	.0008***	.0002	0.1
advweath_d	.2988***	.0119	34.8	.2878***	.0110	33.3	.0096	.0137	1.0	.0405***	.0099	4.1
advweath_a	.3688***	.0120	44.6	.3621***	.0116	43.6	.0373***	.0128	3.8	.0705***	.0109	7.3
Strike_da	.7280***	.0437	107.1	.7160***	.0433	104.6	-.0737***	.0181	-7.1	-.0350**	.0170	-3.4
Lcc	.2368***	.0167	26.7				-.0162	.0300	-1.6			
AB (Air Berlin)				-.1943***	.0221	-17.7				-.0265	.0483	-2.6
FR (Ryanair)				-.1967***	.0261	-17.9				.0617	.0424	6.4
VY (Vueling)				-.1321***	.0277	-12.4				.2658***	.0568	30.4
DY (Norwegian)				-.5969***	.0368	-44.9				-.2806***	.0670	-24.5
LH (Lufthansa)				-.4344***	.0205	-35.2				-.0860**	.0407	-8.2
AF (Air France)				-.4517***	.0275	-36.3				.1536***	.0439	16.6
IB (Iberia)				-.1832***	.0290	-16.8				.2913***	.0577	33.8
KL (KLM)				-.5494***	.0327	-42.3				.0843	.0627	8.8
SK (SAS)				-.6128***	.0290	-45.8				-.2129***	.0440	-19.2
BA (British Airways)				-.1274***	.0243	-12.0				.1653***	.0474	18.0
AZ (Alitalia)				-.2107***	.0350	-19.0				.3771***	.0734	45.8
LX (Swiss)				-.2736***	.0272	-23.9				-.1306***	.0499	-12.2
_cons	2.0832***	.0314		2.3681	.0373		-5.6875***	.1272		2.7325***	.0625	
	Log likelihood = -2288059 Prob > chi2i = 0.0000			Log likelihood = -2272396 Prob > chi2i = 0.0000			Log likelihood = -3954643 Prob > chi2i = 0.0000			Log likelihood = -3926376 Prob > chi2i = 0.0000		
Note: Standard errors are clustered by route and carrier (e.i. AMSMUC, KLM). Regressions included month-specific fixed effects and day-of-week fixed effects (both not reported). *, ** and *** indicate 10%, 5% and 1% significance level.												

Table 5: Regression Output

Regression Results – Individual Carrier Effects (Hypothesis 5)

This section evaluates whether the overall LCC effects from the previous two regressions is driven by a homogenous set of individual OTP. Colloquially spoken, we ask: can we measure all LCCs (and TNCs) with the same yardstick?

To evaluate hypothesis 5 we re-estimate the two regression models for *delay_min_a* and *excess_min* again, using individual individual airline-specific dummy variables instead of the overall LCC dummy variable. We use the largest LCC in the sample, easyJet, as reference. Thus, we drop the easyJet dummy variable from the regression. Results are included in Table 5. Around 80% of the added individual individual airline-specific dummy variables are significant.

We observe that the overall LCC effect in the arrival delay regression is largely driven by a very exceptional performance of easyJet, also considering the large share of easyJet in the sample[31]. This exceptional position is twofold: first, compared to easyJet (and ceretis paribus), all other twelve airlines' flights are less likely to be on-time; second, if delayed, easyJet has a higher expected delay than any other airline in the sample.

If we have a look at excess travel time, easyJet's performance does not stand that much apart from other carriers. Signs of the coefficients are actually mixed across the two carrier groups – some airlines perform better than easyJet, others worse. However, we note that the LCCs are collectively strong when it comes to the probability of on-time arrival[32]. Among them, Ryanair is the best-performing airline of all. This means Ryanair is most likely of all to achieve the minimum possible travel time. Given all that, this explains the large overall LCC effect (around 163% higher odds of having zero excess travel time).

At the same time signs and significances of the coefficients in the negative binomial regression are mixed across airlines. Both LCCs and TNCs as groups are very heterogeneous. The exact minutes of excess travel time seem to vary from airline to airline, rather than from carrier type to carrier type. We find interesting that all LCCs seem to have extraordinary control over the general occurrence of delays. Yet, in case of delay, the exact size of excess travel time is hard to influence for all carriers.

[31] Remember that easyJet is almost twice as large as the second largest LCC in the sample.

[32] E.i. TNCs do consistently perform worse than easyJet, whereas LCCs at least perform „less worse" than all other TNCs, not different from easyJet or better than easyJet.

Throughout the regressions, we observe that the two carrier groups are not very homogenous in their OTP. However, the TNC group seems to be slightly more homogenous. To come to that conclusion, we reviewed standard deviations of the coefficients and variation coefficients (see Table 6). Depending on the regression part and carrier group the variation coefficients (relative standard deviations) vary between (-)20.85% and 936.91%, which we generally consider as quite high. Throughout the analysis, the LCC group has higher variation coefficients (neglecting signs of coefficients), which leads us to the insight that the LCC group is less homogenous than the TNC group.

Dependent variable:		*delay_min_a*		*excess_min*	
Carrier type:		LCC	TNC	LCC	TNC
on-time probability	mean	-37.28	-66.83	-5.58	-58.36
	standard deviation	26.62[33]	13.93	14.84	17.76
	Variation coefficient	-61.84%[34]	-20.85%	-266.13%	-30.43%
	positive coefficient signs	0/4	0/8	1/4	0/8
size of delay in case of delay	mean	-23.23	-28.91	2.43	10.43
	standard deviation	14.67	12.62	22.72	22.78
	Variation coefficient	-63.18%	-43.64%	936.91%	218.51%
	positive coefficient signs	0/4	0/8	2/4	5/8

Table 6: Analysis of coefficients (coeff. (%)) in regression models

To sum up; it is difficult to generalize across carriers of the same carrier groups. Instead, we have to be careful when assuming that the overall LCC effects from hypothesis 3 and 4 reflect all LCCs' performance in equal measures. Accordingly, we reject hypothesis 5 and note instead: the overall LCC OTP is only to some extent driven by a homogenous set of individual OTP.

[33] $S = \frac{1}{4-1}((-69.4-(-37.28))^2 + (-21-(-37.28))^2 + (48.1-(-37.28))^2 + (-10.6-(-37.28))^2) = 26.62$

[34] $Variation\ coefficient = \frac{standard\ deviation\ S}{mean}$

7 Conclusion

This paper aims at extending knowledge of the link between airline business models and service quality. It specifically asks whether LCCs are more punctual than TNCs. Previous research has not answered this question for the European case so far. Therefore, this paper complements existing research and adds transparency and accuracy to simple OTP rankings that are available on the internet.

As a first glance, a basic two-mean comparison of the share of arrival delays reveals that on average LCCs perform better than TNCs. Only 31% of LCCs' flights arrive at least one minute behind schedule, whereas TNCs' flights are in 45% of all cases delayed. LCCs' expected arrival delay is around one minute smaller than the one of TNCs. Depending on which variable we focus on easyJet is either best performer or worst performer: among all airlines, easyJet has the lowest share of delayed arrivals. At the same time, if delayed, easyJet's flights have the highest average delay (21.39 min) of all airlines.

In our literature review we found indication that LCC's strong results may be embedded in the LCC business model. Most importantly, serving uncongested airports and routes is expected to lead to an OTP advantage compared to TNCs. As a reaction to that, we extended our statistical analysis towards a more formal regression analysis, controlling for airport variables as well as economic, logistical and weather variables.

Even after controlling for some factors, our results follow the direction of the mean comparison. In fact, we predict a higher probability of on-time arrival for LCCs than for TNCs. Under equal circumstances, LCC flights' odds of being on-time are around 120% higher than TNC flights'. Yet, we confirm what we found before: those LCC flights that may potentially suffer from delay tend to have higher average arrival delays than TNCs (ca. 27% higher).

With the so far mentioned OTP metrics our results may be spurious as airlines are able to manipulate by including longer buffer times than others. To account for this, we introduced excess travel time as an OTP metric that is unaffected by so-called "schedule padding". Using excess travel time changes our results even more in favor of LCCs. If LCCs and TNCs operate under equal circumstances, LCCs are more likely to achieve the minimum feasible travel time.

This paper also finds considerable evidence that the overall LCC effect that we have investigated is not driven by an entirely homogenous group of individual LCCs. This makes it difficult to generalize within the LCC group. Our conclusion about individual airline-specific effects is mainly threefold. First, the overall LCC effect is mostly in line with easyJet's individual performance. This is due to the fact that easyJet contributes most LCCs observation to the sample. Second, LCCs are collectively strong when it comes to the probability of on-time arrival. Third, the TNC group is slightly more homogenous than the LCC group.

7.1 Implications for Practice and Policy

This paper argues that airline OTP data should be publicly available. It calls on EU Institutions to make airlines publish OTP statistics on a regular basis. In the current situation scholars and passengers have strong difficulties in gathering OTP data. For passengers this results in a lack of transparency. For researcher it limits the opportunities to investigate OTP systematically. Only if OTP data becomes available, OTP research for the European airline industry is able to become more mature.

7.2 Limitations and Future Research

Our proposed methodology could clearly be further developed. We identified four major limitations that might be a starting point for adaptions.

First, our research did not consider any performance gap between LCCs and TNCs when it comes to cancellation. Instead, cancelled flights have been fully excluded from the analysis right from the beginning. Thereby, we follow Mazzeo (2003), arguing that it is hard to include cancelled and completed flights in the same analysis without making assumptions about comparability of such flights. However, we suggest future research to investigate cancelled flights as well.

Second, we are aware that our delay variables might not be a good approximation for passenger travel experience. In accordance with that, Wang (2007) notes that regular delay variables tend to underestimate the real penalties of missed connections that occur because of late arrival. Our research ignores this as it investigates OTP from a system performance perspective. Yet, we conclude that future research on passengers' perception of OTP and passenger trip delay metrics might be an interesting complement to this research.

Third, we are aware that the OTP advantage of LCCs may vanish with the inclusion of airport-specific effects[35]. Due to constraints in computing power we were not able to include such effects. Therefore, we remain careful with our interpretation and suggest future research to take up this point. However, if we assume the OTP advantage of LCCs' not to vanish, we may attribute a part of LCCs' strong performance to such factors as fleet age, maintenance procedures or process efficiency.

Fourth, we neglected some other factors that might have an influence on airlines' OTP and airlines do not have explicit control of. Such are, for instance, different national air transport regulations. We assumed airlines to face exact the same rules in their origin country and at the airports they serve.

[35] These variables account for unobserved airport specific effects. Rupp & Sayanak (2008) bring in airport equipment, maintenance facilities, and airport capacity as such effects. Models would have been estimated with and without airport dummies. This comparison allow to answer the following question: to what extent is an airline's arrival delay driven by the particular airports that airline is serving (Rupp & Sayanak, 2008)? Even though Rupp and Sayanak did not find that LCCs registered longer arrival delays or excess travel time after controlling, we may face exactly this effect for Europe.

8 References

Beatty, R., Hsu, R., Berry, L., & Rome, J. (1998). *Preliminary evaluation of flight delay propagation through an airline schedule*. *Second USA/Europe Air Traffic Management RandD Seminar*. Orlando.

Brons, M., & Rietveld, P. (2007). *Betrouwbaarheid en klanttevredenheid in de OV-keten: een statistische analyse. Internal research report for the Transumo project Betrouwbaarheid van transportketens*. Vrije Universiteit Amsterdam.

Burghouwt, G., Hakfoort, J., & Ritsema van Eck, J. (2003). The spatial configuration of airline networks in Europe. *Journal of Air Transport Management*, *9*(5), 309-323. doi:10.1016/S0969-6997(03)00039-5

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconomics Using Stata - Revised Edition*. College Station: Stata Press.

Casadesus-masanell, R., & Ricart, J. E. (2010). From Strategy to Business Models and onto Tactics. *Long Range Planning*, *43*(2-3), 195-215. Elsevier Ltd. doi:10.1016/j.lrp.2010.01.004

Caulkins, J. P., Barnett, A., Larkey, P. D., Yuan, Y., & Larkey, D. (1993). The On-Time Machines: Some Analyses of Airline Punctuality. *Operations Research*, *41*(4), 710-720.

Cook, A. J., & Tanner, G. (2011). *European airline delay cost reference values*. Retrieved from http://westminsterresearch.wmin.ac.uk/9325/

Dobruszkes, Ã. (2009). Does liberalisation of air transport imply increasing competition ? Lessons from the European case, *16*, 29-39. doi:10.1016/j.tranpol.2009.02.007

Gillen, D., & Lall, A. (2004). Competitive advantage of low-cost carriers: some implications for airports. *Journal of Air Transport Management*, *10*(1), 41-50. doi:10.1016/j.jairtraman.2003.10.009

Graham, B., & Vowles, T. M. (2006). Carriers within Carriers: A Strategic Response to Low- cost Airline Competition. *Transport Reviews*, *26*(1), 105-126. doi:10.1080/01441640500179377

IATA. (2010). *Worldwide Scheduling Guidelines Effective January 2010 19 th Edition*.

Ito, H., & Lee, D. (2003). Incumbent Responses to Lower Cost Entry : Evidence from the U . S . Airline Industry ∗ .

Lee, D. (2003). Low Cost Carrier Growth in the U . S . Airline Industry : Past , Present , and Future.

Mayer, C., & Sinai, T. (2002). Network Effects, Congestion Externalities, and Air Traffic Delays: Or Why All Delays Are Not Evil.

Mazzeo, M. J. (2003). Competition and Service Quality in the U . S . Airline Industry. *Review of Industrial Organization*, *22*, 275-296.

Olsson, N. O. E., & Haugland, H. (2004). Influencing factors on train punctuality—results from some Norwegian studies. *Transport Policy*, *11*(4), 387-397. doi:10.1016/j.tranpol.2004.07.001

Performance Review Commission. (2005). Report commissioned by the Performance Review Commission Report on Punctuality Drivers at Major European Airports, (May).

Performance Review Commission. (2012). Prr 2011 Performance Review Report, (May).

Rupp, N. G. (2001). Does Competition Infleuence Airline On-Time Performance ?

Rupp, N. G. (2007). Investigating the Causes of Flight Delays.

Rupp, N. G. (2009). Do carriers internalize congestion costs? Empirical evidence on the internalization question. *Journal of Urban Economics*, *65*(1), 24-37. Elsevier Inc. doi:10.1016/j.jue.2008.07.003

Rupp, N. G., & Sayanak, T. (2008). Do Low Cost Carriers Provide Low Quality Service? *Revista de Análsis Económico*, *23*(1), 3-20.

Röhner, P. (2009). *Modelling of punctuality at Frankfurt Airport*.

Santos, G., & Robin, M. (2010). Determinants of delays at European airports. *Transportation Research Part B: Methodological*, *44*(3), 392-403. Elsevier Ltd. doi:10.1016/j.trb.2009.10.007

Sherry, L., Wang, D., Xu, N., & Larson, M. (n.d.). Statistical Comparison of Passenger Trip Delay and Flight Delay Metrics.

Spehr, U. (2003). *Analyse des Wettereinflusses auf die Pünktlichkeit Flugverkehr*. Universität Hannover.

Thrasher, T., & Weiss, W. (n.d.). A Proposed Method for Measuring Air Traffic Delay.

Tretheway, M. W. (2004). Distortions of airline revenues : why the network airline business model is broken, *10*, 3-14. doi:10.1016/j.jairtraman.2003.10.010

Wang, D. (2007). Methods For Analysis Of Passenger Trip Performance In A Complex Networked Transportation System.

Williams, G. (2001). Will Europe's charter carriers be replaced by "no-frills" scheduled airlines? *Journal of Air Transport Management*, *7*(5), 277-286. doi:10.1016/S0969-6997(01)00022-9

Wu, C.-L. (2005). Inherent delays and operational reliability of airline schedules. *Journal of Air Transport Management*, *11*(4), 273-282. doi:10.1016/j.jairtraman.2005.01.005

Wu, C.-L., & Caves, R. E. (2003). Flight schedule punctuality control and management: a stochastic approach. *Transportation Planning and Technology*, *26*(4), 313-330. doi:10.1080/03081060310001635869

Zeithaml, V. A. (1981). How Consumer Evaluation Processes Differ between Goods and Services. *Marketing of Services, J. Donnelly and W. George* (pp. 186-190).

9 Appendix

***Appendix A**: CODA Delay Causes*

	CODA Cause	Description	IATA Code
Primary Delays	Airlines	Passenger and Baggage	11-19
		Cargo and Mail	21-29
		Aircraft and Ramp Handling	31-39
		Technical and Aircraft Equipment	41-49
		Damage to Aircraft & EDPI/Automated Equipment Failure	51-58
		Flight Operations and Crewing	61-69
		Other Airline Related Causes	Others
	Airport	ATFM due to Restriction at Departure Airport	83
		Airport Facilities	87
		Restrictions at Airport of Destination	88
		Restrictions at Airport of Departure	89
	En-Route	ATFM due to ATC En-Route Remand/Capacity	81
		ATFM due to ATC Staff / Equipment En-Route	82
		Security and Immigration	85-86
	Weather	Weather (other than ATFM)	71-79
		ATFM due to Weather at Destination	84
	Miscellaneous	Miscellaneous	98-99
Reactionary Delays	Reactionary	Late Arrival of Aircraft, Crew, Passengers or Load	91-96

Appendix B: *Passenger Traffic by Airline*

Airline	**Monthly Passenger Traffic in millions (ca.)**	**Reference month**
Air France-KLM Group	6[36] (jointly)	
International Airlines Group (Iberia-British Airways)	5.1[37] (jointly)	
Lufthansa	5[38]	December 2012
Ryanair	4.8[39]	December 2012
easyJet	4.3[40]	December 2012
Alitalia	1.95[41]	approximated from 2010 statistics
Scandinavian Airlines	1.8[42]	approximated from November 2012 - January 2013 statistics
Air Berlin	1.7[43]	December 2012
Norwegian Air Shuttle ASA	1.3[44]	December 2012
Swiss International Air Lines	1.2[45]	December 2012
Vueling Airlines	0.9[46]	December 2012

Note: Turkish Airlines and Aeroflot have comparatively high monthly passenger numbers but are excluded because this research focusses on Western-European airlines.
Note II: The TNCs Austrian Airlines and Swiss are part of the Lufthansa group but excluded because of their low individual passenger numbers. Germanwings, which also belongs to the Lufthansa group, is not part of the sample because we neglect low cost affiliates of TNCs.

[36] http://www.airfranceklm-finance.com/en/Financial-information/Press releases?theme%5B%5D=Traffic&annnes=2012&x=14&y=12
[37] http://www.iairgroup.com/phoenix.zhtml?c=240949&p=irol-rnsArticle_Print&ID=1771747&highlight
[38] http://investor-relations.lufthansagroup.com/en/finanzberichte/traffic-figures.html
[39] http://www.ryanair.com/en/news/ryanair-december-traffic-up-2-percent
[40] http://corporate.easyjet.com/investors/monthly-traffic-statistics/2012/december.aspx?sc_lang=en
[41] http://de.wikipedia.org/wiki/Alitalia
[42] http://feed.ne.cision.com/wpyfs/00/00/00/00/00/1E/18/0E/wkr0006.pdf
[43] http://ir.airberlin.com/en/ir/facts-about-the-group/traffic-statistics/2012/December
[44] http://www.norwegian.no/Global/norway/omnorwegian/dokumenter/trafficinformation/ 2012/Traffic%20Figures%20DEC%202012.pdf
[45] http://investor-relations.lufthansagroup.com/en/finanzberichte/traffic-figures.html
[46] http://investors.vueling.com/media/9491/vueling_traffic_dec_2012_en_.pdf

Appendix C: *Variable Definition*

Cate-gory		Variable	Unit	Definition	Share of tot. sample	Mean	Stand. dev.
Airport Variables	Slot Coordination	*lev1_d*	0;1 ▲	whether the departure airport is non-coordinated	7.96%		
		lev2_d	0;1 ▲	whether the departure airport is schedule facilitated	14.68%		
		lev3_d	0;1 ▲	whether the departure airport is coordinated	77.35%		
		lev1_a	0;1 ▲	whether the arrival airport is non-coordinated	78.30%		
		lev2_a	0;1 ▲	whether the arrival airport is schedule facilitated	13.94%		
		lev3_a	0;1 ▲	whether the arrival airport is coordinated	7.76%		
	Airport Hubs	*nhub_ d*	0;1 ▲	whether the observed flight departs from a non-hub airport (number of destination ≤ 25)	8.67%		
		shub_d	0;1 ▲	whether the observed flight departs from a small hub airport (25 > number of destinations ≤ 45)	13.38%		
		mhub_d	0;1 ▲	whether the observed flight departs from a medium hub airport (45 > number of destinations ≤ 70)	11.68%		
		lhub_d	0;1 ▲	whether the observed flight departs from a large hub airport (number of destinations > 70)	66.27%		
		nhub_a	0;1 ▲	whether the observed flight arrives at a non-hub airport (number of destination ≤ 25)	8.78%		
		shub_a	0;1 ▲	whether the observed flight arrives at a small hub airport (25 > number of destinations ≤ 45)	12.89%		
		mhub_a	0;1 ▲	whether the observed flight arrives at a medium hub airport (45 > number of destinations ≤ 70)	11.65%		
		lhub_a	0;1 ▲	whether the observed flight arrives at a large hub airport (number of destinations > 70)	66.69%		
	Airline Hubs	*airl_nhub_d*	0;1 ▲	whether the observed flight departs from a non-hub airport (number of destination ≤ 25)	62.67%		
		airl_shub_d	0;1 ▲	whether the observed flight departs from one of its own small hub airport (25 > number of destinations ≤ 45)	11.07%		
		airl_mhub_d	0;1 ▲	whether the observed flight departs from one of its own	14.83%		

				medium hub airport (45 > number of destinations ≤ 70)			
		airl_lhub_d	0;1 ▲	whether the observed flight departs from one of its own large hub airport (number of destinations > 70)	11.43%		
		airl_nhub_a	0;1 ▲	whether the observed flight arrives at a non-hub airport (number of destination ≤ 25)	62.34%		
		airl_shub_a	0;1 ▲	whether the observed flight arrives at one of its own small hub airport (25 > number of destinations ≤ 45)	10.95%		
		airl_mhub_a	0;1 ▲	whether the observed flight arrives at one of its own medium hub airport (45 > number of destinations ≤ 70)	14.47%		
		airl_lhub_a	0;1 ▲	whether the observed flight arrives at one of its own large hub airport (number of destinations > 70)	12.24%		
Economic/Competitive Variables	Route Compet.	*mon*	0;1 ▲	whether the observed flight operates on a monopoly route (served by just one carrier)	27.94%		
		duo	0;1 ▲	whether the observed flight operates on a duopoly route (served by two carriers)	35.24%		
		>2comp	0;1 ▲	whether the observed flight operates on a competitive route (served by more two carriers)	36.82%		
	HHI	*hhi_d*	[0,1] ►	Herfindahl-Hirschmann-Index at departure		.22	.12
		hhi_d	[0,1] ►	Herfindahl-Hirschmann-Index at arrival		.22	.12
Logistical Variables		*flightt*	Min ►	Time from gate push-back time at departure until gate arrival at destination		93.60	47.94
		normdept	[0,1] ►	Normalized departure time (00:00 equal 0; 23:59 equals 1)		.57	.20
		dist	Km►	approximate flight distance between arrival and departure airport		796.20	512.24
		seatcap	►	approximate number of seats available based on airplane type (individual airline-specific adjustments are not accounted for)		149.48	46.21
	Days of Week	*mon*	0;1 ▲	whether observed flight takes place on Monday	14.81%		
		tue	0;1 ▲	whether observed flight takes place on Tuesday	14.36%		
		wed	0;1 ▲	whether observed flight takes place on Wednesday	14.96%		

	thu	0;1 ▲	whether observed flight takes place on Thursday	15.11%
	fri	0;1 ▲	whether observed flight takes place on Friday	15.22%
	sat	0;1 ▲	whether observed flight takes place on Saturday	11.87%
	sun	0;1 ▲	whether observed flight takes place on Sunday	13.68%
Weather Variables	*advweath_d*	0;1 ▲	whether the departure airport is affected by adverse weather on the observed day	6.58%
	advweath_a	0;1 ▲	whether the arrival airport is affected by adverse weather on the observed day	6.69%
Other	*strike_da*	0;1 ▲	whether the departure and/or arrival airport is affected by strike on the observed day	.43%
	lcc	0;1 ▲	**whether observation is a LCC flight (main independent variable)**	**30.67%**

▲ Dummy variable; ► Continuous or discrete variable
No missing data for any of the variables (n=1 056842)

Appendix D: *Herfindahl-Hirschman Index*

Concentration in our analysis refers to airport concentration and is measures by the Herfindahl-Hirschman index (HHI). The two HHI variables per OTP observation represent both the origin and destination airports' concentration during the first week of March 2012. We chose the one-time calculation due to limited data constraints. The value is used as proxy for the entire period of observation. As opposed to Mazzeo (2003) the HHI in our analysis is not based on revenue but simply on the number of connections from a particular airport. The index is defined as the sum of the squared individual market shares of all airlines serving a particular airport as the following equation expresses:

$$HHI_a = \sum_{j=1}^{N} s_{ja}$$

Where s_{ja} denotes the market share of carrier *j* at airport *a* and *N* is the number of airlines operating at the airport. Accordingly, airports with low concentration levels are used by many airlines with small market share. Highly concentrated airports, in contrast, are dominated by only a handful of carriers.

Appendix E: *Using 15 minutes allowance as delay definition*

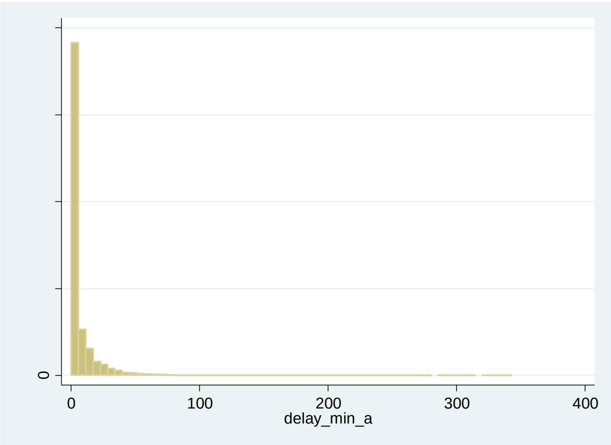
If we shift now to 15 minutes allowance (*del>=15_01_a*) we see that the ranking partly changes (results not included in Table 4). Changes for the arrival ranking are largely at EasyJet's charge: while easyJet was the top performer before, other airlines are now better ranked. For instance, SAS has the lowest proportion of flights delayed by 15 minutes or more. This superior performance of SAS is in line with what is often communicated in the media. After SAS Norwegian Airlines follows. British Airways and Iberia perform worst in this ranking. Europe's largest LCCs Ryanair and easyJet take positions in the upper half of the ranking.

Appendix F: *Pairwise Correlation Analysis*

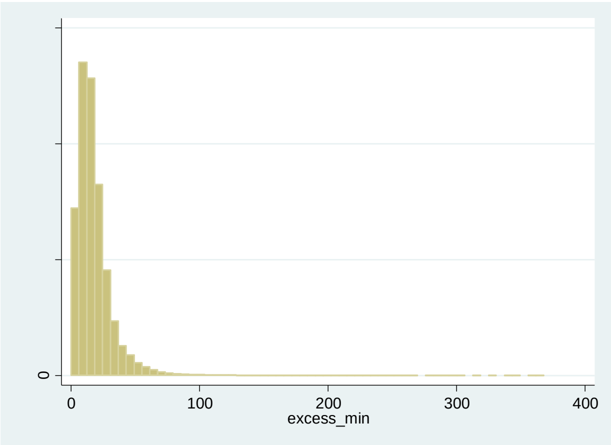
	delay_min_d	*del>=1_01_d*	*del>=15_01_d*	*delay_min_a*	*del>=1_01_a*	*del>=15_01_a*	*excess_min*
delay_mind_d	1						
del>=1_01_d	.465	1					
del>=15_01_d	.722	.4271	1				
delay_min_a	.855	.3025	.5486	1			
del>=1_01_a	.4111	.4217	.4192	.5098	1		
del>=15_01_a	.6124	.4271	1	.7367	.4192	1	
excess_min	.0031	-.0035	.0078	.2027	.2128	.0078	1
lev1_d	-.044	-.0735	-.0446	-.0395	-.0584	-.0446	-.0815
lev2_d	-.0536	-.1244	-.0568	-.0231	-.0512	-.0568	-.0789
lev3_d	.0738	.1527	.0768	.0451	.081	.0768	.1195
lev1_a	-.0184	-.0077	-.0171	-.0302	-.0283	-.0171	-.0571
lev2_a	-.0028	.0025	-.0076	-.0116	-.0161	-.0076	-.0634
lev3_a	.0143	.0028	.0175	.0294	.0319	.0175	.0903
nhub_ d	-.0434	-.0911	-.0437	-.0114	-.0207	-.0437	-.0778
shub_d	-.0239	-.0655	-.0278	-.0315	-.0626	-.0278	-.0552
mhub_d	.0022	-.0404	.0062	-.0123	-.0403	.0062	.0124
lhub_d	.0415	.1289	.0418	.0378	.0848	.0418	.0777
nhub_a	-.0226	-.0155	-.0244	-.005	.0113	-.0244	-.0691
shub_a	-.0005	.0143	-.0003	-.0213	-.0296	-.0003	-.0283
mhub_a	.0115	.0143	.0131	-.0129	-.0344	.0131	-.0041
lhub_a	.0061	-.0106	.006	.0269	.0377	.006	.0644
airl_nhub_d	-.0172	-.0942	-.0194	.0057	-.0265	-.0194	-.0187
airl_shub_d	-.028	-.0516	-.0322	-.0185	-.0429	-.0322	.0107
airl_mhub_d	.0528	.1133	.0617	.0128	.0405	.0617	.0557
airl_lhub_d	-.0053	.0675	-.0077	-.0048	.0373	-.0077	-.0442
airl_nhub_a	.0041	.0443	-.0001	.0327	.0563	-.0001	-.0036
airl_shub_a	.0234	.0105	.027	-.013	-.0385	.027	.0422
airl_mhub_a	.0033	-.0214	.0041	-.0046	-.0026	.0041	-.0115
airl_lhub_a	-.0319	-.0526	-.0301	-.0311	-.0437	-.0301	-.0226
mono	-.0054	-.0531	-.0003	-.0308	-.0743	-.0003	-.065
duo	-.0016	-.0012	-.0041	-.0069	-.0049	-.0041	-.0132

>2comp	.0066	.0506	.0043	.0355	.074	.0043	.0735
hhi_d	-.0275	-.0493	-.0211	-.0243	-.0375	-.0211	-.0624
hhi_a	-.0075	-.007	-.0031	-.0286	-.0444	-.0031	-.0578
normdept	.0814	.0349	.0916	.0629	.0384	.0916	.0388
dist	.0808	.091	.0931	.0308	.0032	.0931	.1654
seatcap	.0911	.1305	.1011	.048	.0419	.1011	.1544
mon	-.0098	-.0091	-.0117	-.0091	-.0084	-.0117	-.0072
tue	-.039	-.0455	-.0406	-.0334	-.0394	-.0406	-.0332
wed	-.0168	-.0208	-.0177	-.0117	-.0112	-.0177	-.0122
thu	-.0054	-.0029	-.0036	-.0008	.0083	-.0036	-.0012
fri	.0373	.0334	.0325	.0364	.0373	.0325	.0306
sat	.0213	.0293	.0267	.0103	.0088	.0267	.015
sun	.0139	.0178	.0165	.0087	.0046	.0165	.0091
advweath_d	.0709	.0714	.064	.0772	.0816	.064	.0576
advweath_a	.0607	.0323	.0561	.081	.0689	.0561	.0601
strike_da	.0333	.0103	.0157	.031	.0104	.0157	.0185
lcc	.0856	.0473	.0967	-.0316	-.1273	.0967	.085
apr	.0049	-.0048	.0002	.012	.0046	.0002	-.0098
may	-.0213	-.0328	-.0219	-.0107	-.0126	-.0219	-.0268
jun	.014	.0194	.0164	.0233	.0371	.0164	.0146
jul	.0381	.0345	.0334	.0311	.0234	.0334	.0479
aug	-.0183	-.0096	-.0157	-.0364	-.0444	-.0157	-.0266
sep	-.0132	-.003	-.0089	-.0135	-.0044	-.0089	.0056

Appendix G: *Histograms Dependent Variables*



Histogram *delay_min_a*



Histogram *excess_min*