EXAMINING THE EFFECTS OF MARKET CONCENTRATION ON DEPARTURE AND ARRIVAL ON-TIME PERFORMANCE AT LARGE AIRPORTS

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ABSTRACT

This study explores the relationship between market concentration and on-time performance at major airports. It investigates whether higher market concentration levels are associated with improved or worsened flight punctuality. The research is based on extensive data from various airlines operating at these airports and provides valuable insights for airport operators, airlines, and policymakers. The findings indicate that variation in market concentration significantly impacts on-time performance. On-time performance decreases to approximately 0.6 to 0.7 in markets with heightened concentration and reduced competition. However, moderately concentrated markets demonstrate higher competition and relatively high on-time performance. These results provide policymakers with opportunities to enhance overall system performance through strategic interventions.

KEYWORDS

departure on-time performance; arrival on-time performance; market concentration; large airports; Herfindahl Hirschman index; market dominance

1. INTRODUCTION

The airline industry allows global connectivity and the movement of people and goods over long distances and is an essential component of modern transportation. Despite advancements in technology and infrastructure, the industry concerns about the industry's efficiency and reliability remain, particularly in terms of departure and arrival punctuality. Delays and disruptions inconvenience passengers, have significant economic implications for airlines, and have broader implications for the aviation ecosystem (Suzuki, 2000).

Timely departures and arrivals are critical for airlines to maintain operational efficiency, ensure passenger happiness, and reduce costs (Suzuki, 2000). A delay in the intended departure time can cause a chain reaction of delays and disturbances across the network (N. Kafle, 2016), resulting in missed connections, greater fuel consumption, and decreased aircraft utilization. On the other hand, delays in arrival might have a domino effect, influencing subsequent flights and passenger schedules.

Furthermore, delays and cancellations can result in financial penalties, compensation claims, and reputational harm to the airline. As the world's largest domestic market, the US costs 30 billion USD annually due to delays, which is a considerable burden for stakeholders (Ball Michael, 2010).

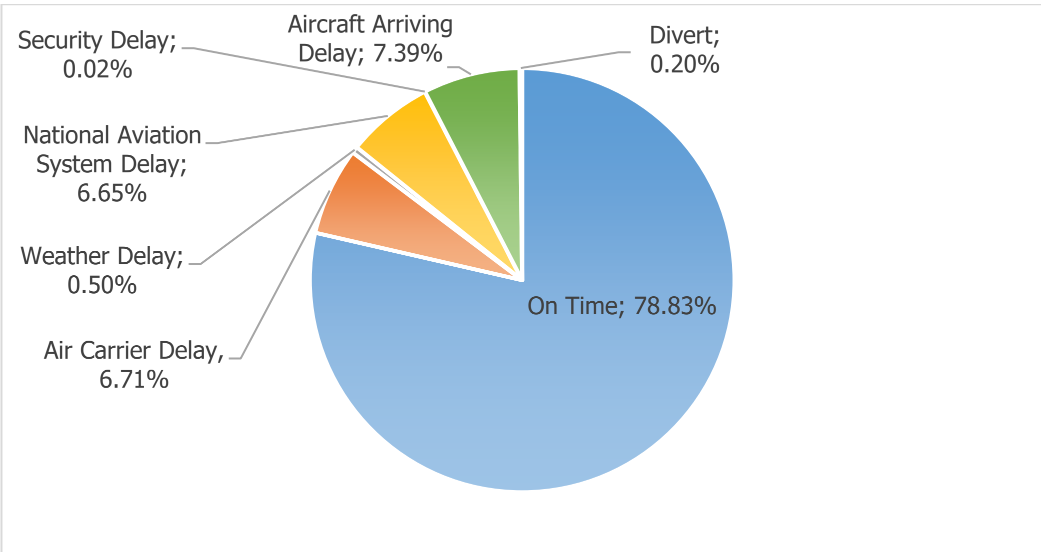

Figure 1: On-time performance during April 2017

Data from the FAA (Federal Aviation Association) provide six main reasons for flights' on-time performance. The delay can occur due to air carriers, weather, the national aviation system, security delays, aircraft arrival delays, and diverts. As per FAA data, air carrier delays, national aviation system delays, and aircraft arrival delays were significant among these reasons (Figure 1). From the mentioned causes, the study focuses on areas that air carriers can control.

The air carrier delay can be grouped into several subcategories. Examples of occurrences that may determine carrier delay are aircraft cleaning, aircraft damage, awaiting the arrival of connecting passengers or crew, baggage, bird strike, cargo loading, catering, computer, outage-carrier equipment, crew legality (pilot or attendant rest), damage by hazardous goods, engineering inspection, fueling, handling disabled passengers, late crew, lavatory servicing, maintenance, over sales, potable water servicing, removal of unruly passengers, slow boarding or seating, stowing carry-on baggage, and weight and balance delays (FAA, 2020).

Many reasons can explain carrier delays. The present study attempts to determine how market concentration affects departure and arrival delays because the impact of airline market concentration on on-time performance has received less attention. The degree of dominance exercised by a few airlines or carriers within a specific market or geographical area is referred to as market concentration. In a highly concentrated market, a small number of firms dominate a sizable percentage (Mark Hansen, 2015), potentially resulting in less competition and weakened incentives for operational efficiency.

Recognizing the connection between market concentration and departure and arrival on-time performance is critical for various reasons. For starters, it illuminates the dynamics of the airline business, providing insights into the competitive landscape and the possible impact on operational efficiency. Second, it assists airlines and industry stakeholders in identifying and addressing any adverse effects of market concentration, such as poorer service quality or higher prices. Third, it provides essential information to policymakers to establish and implement appropriate regulations and policies that foster competition and improve operational efficiency.

This research paper intends to contribute to the current literature and fill gaps in our understanding of this relationship by thoroughly examining the impact of market concentration on departure and arrival on-time performance at large airports. The study findings can help airlines, passengers, and policymakers establish strategies and policies to increase timeliness, improve the passenger experience, and foster healthy competition in the airline business. The market concentration is a hidden force capable of reshaping the market itself. Researchers in this study aim to see how the market concentration affects the overall on-time performance of flight operations.

In summary, the background and significance of this research can be found in recognizing the importance of departure and arrival punctuality in the airline industry, the potential impact of market concentration on operational efficiency, and the need for scientific evidence to inform decision-making and policy development. This study seeks to provide significant insights into the consequences of market structure on the functioning of large airports and the broader aviation ecosystem by investigating the relationship between market concentration and on-time performance. This study intends to cover four objectives:

1. To calculate the market share for each operation day, operating between large airports.
2. To calculate market concentration by using the first objective's results.
3. To identify separate market segments inside short-haul OD pairs.
4. To identify how market concentration affects OTP (On-Time Performance) from perfect competition to imperfect competition.

Collectively, these objectives aim to contribute to understanding how this hidden force shapes airline operation performance at large airports while suggesting practical implications for industry stakeholders to mitigate the inefficiencies of overall operations.

This study aims to contribute to the existing literature on airline operations, competition, and market structure by addressing the research problem. It aims to provide empirical evidence and a thorough understanding of the impact of market concentration on departure and arrival on-time performance at large airports. Finally, these study findings can provide valuable insights and inform decision-making processes for airlines, passengers, and policymakers seeking to improve punctuality and overall airline industry performance.

2. LITERATURE REVIEW

2.1. ON-TIME PERFORMANCE

Customer happiness is essential to the success of a service industry company, such as commercial aviation. However, this industry is sensitive to the external environment; for example, the civil aviation industry faced a massive challenge among other modes of transportation with the immediate impact of COVID-19 (M.Mavin De Silva, 2023). Airlines must maintain a high level of service across all their vehicles to keep their customers happy. The most notable characteristic of the industry is punctuality in performance. The world's largest domestic aviation market incurred approximately $30 billion annually in delay costs (Ball Michael, 2010). This proves that OTP is a critical output of aviation as well as any transport-related industry. In aviation, on-time performance can be a competitive edge of the airline against competitors because travelers choose flights based on their preferred arrival time due to the purpose of the travel (Lu Hao, 2014). Airlines heavily rely on the number of passengers they can carry on their flights regarding revenue, draw in new business, and keep existing clients. They must ensure on-time departure of their flights since delays can lead to lost sales, bad feedback, and a tarnished reputation (Jakub Haijko, 2020).

Airlines must prioritize safety measures in addition to on-time performance to guarantee the trust and loyalty of their customers—regular maintenance inspections, thorough security checks, and knowledgeable staff are all part of this. Airlines can position themselves as dependable and trustworthy options for travelers by prioritizing both on-time performance and safety measures. By putting money into technology like real-time flight tracking systems, airlines can spot potential delays and take proactive measures to fix them before they become major problems (N. Kafle, 2016).

Overall, the aviation sector's success depends on keeping a laser-like focus on both operational effectiveness and customer satisfaction (Chow, 2015). Achieving high OTP results from the success of a highly disruptive process. The risk of losing OTP is significantly high. Therefore, knowing how the particular route will perform under a specific condition is worthwhile, just like a real-time risk assessment system (Vihan Weerapura, 2023).

2.1.1. CALCULATING ON-TIME PERFORMANCE

On-time performance calculations are different from a general point of view. The International Civil Aviation Organization (ICAO) has implemented a 15-minute rule as a safety-first operation (ICAO, 2017). This rule explains that a flight will be considered an on-time performance if the flight's actual departure or arrival time is within (±15) minutes of the scheduled time (Cheng-LungWu, 2010).

2.2. MARKET CONCENTRATION IN THE AIRLINE INDUSTRY

In any deregulated market, market concentration determines the distribution of negotiation power between consumer and supplier (Doganis, 2010). The supplier and consumer may change based on the situation, but behavior will not change because the power of negotiation decides the behavior. Based on the concentration level, we can label the market structure as a 'perfect competition market' or 'imperfect competition market'. In other terms, oligopoly markets and monopoly markets (Tamotsu Onozaki, 2003). With the deregulation of civil aviation in 1978, the market has behaved the same way as explained above.

2.2.1. CALCULATION OF MARKET CONCENTRATION

The Herfindahl-Hirschman Index (HHI) and concentration ratios are the most frequently used metrics by researchers to measure market concentration. The HHI determines market concentration by multiplying the squared market shares of various companies engaged in a market. A higher HHI value indicates greater concentration, implying that a few dominant companies control a sizable portion of the market. The market share held by a predetermined number of top companies is calculated by concentration ratios, which provide a simpler measurement. These quantitative measures of market concentration enable researchers to compare market concentration levels across different markets and historical periods (Ismail, 2017). Based on HHI value, the market can be categorized into three market structures as follows: (Bromberg, 2023)

- Unconcentrated markets: HHI <0.15 (high competition)
- Moderately concentrated markets: HHI between 0.15 ⩽ HHI<0.25 (medium competition)
- Highly concentrated markets: HHI ⩾0.25 (low competition)

$$HHI = \sum_{i=1}^{n} MS(i)^2$$

Equation 1. Herfindahl-Hirschman Index (HHI)

Equation (1) illustrates how to calculate the concentration index, where MS(i) is the market share of the 'i' airline for the OD market. As mentioned above, market concentration levels give us an idea of the market competition level.

2.3. THE RELATIONSHIP BETWEEN MARKET CONCENTRATION AND OPERATIONAL PERFORMANCE

Numerous studies revealed that airline schedules were more likely to be padded to account for airborne and surface delays in competitive markets to improve the operation performance or, in other terms, to increase the OTP (Skaltsas, 2011) (Thomas Morisset, 2011). Parallel to this study, another investigation in 2012 identified that an increase in market share in a particular OD market negatively impacts the OTP. They specifically realized that a higher market share leads to the rise of overage and underage cost ratio, thus reducing the likelihood of OTP (Deshpande & Arikan, 2012). These findings perfectly align with (Mazzeo, 2003) that additional competition positively correlates with OTP, which aids the airline in gaining market share, and the authors concluded that a monopolistic market illustrates OTP.

Conversely, some studies argue that competition worsens OTP, and a market with less competition illustrates high OTP (Rupp, Owens, & Plumly, 2006) (rince & Simon, 2014). Based on this literature, a correlation between market share and on-time performance is evident, as discussed in (Cheng-LungWu, 2010). Even though controversial, it is clear that on-time performance impacts airline market share. These controversial results make us doubt the methodologies authors have followed to analyze market concentration data. According to our observations in Equation 1, HHI will not produce linear results, as explained in (Yadav, Acharya, & Acharya, 2021). However, all authors we mentioned in the aviation research field have utilized OLS regression to analyze data. This could be the underlying reason for such controversial results. These results signify that starting with comparison is better. Hence, this study compares the HHI and OTP results to get a clear idea.

We identified another research gap regarding the categories of airports. In previous studies, we could not determine how a researcher can overcome this issue. Therefore, the analyses were performed without physical factors because we think different airport categories will perform differently with the concentration level. Researchers in this study aim to determine how concentration affects when departure and arrival occur only at large airports. We assume that the airport categories at the same level will respond similarly. Since airlines facing competition tend to allocate more resources to ensure timely departures and arrivals to attract and retain customers, as mentioned in this study, we assume that the airports of the same category could provide the same level of service for each airline. Thus, the main objective of this study is to understand the on-time distribution against concentration.

3. METHODOLOGY

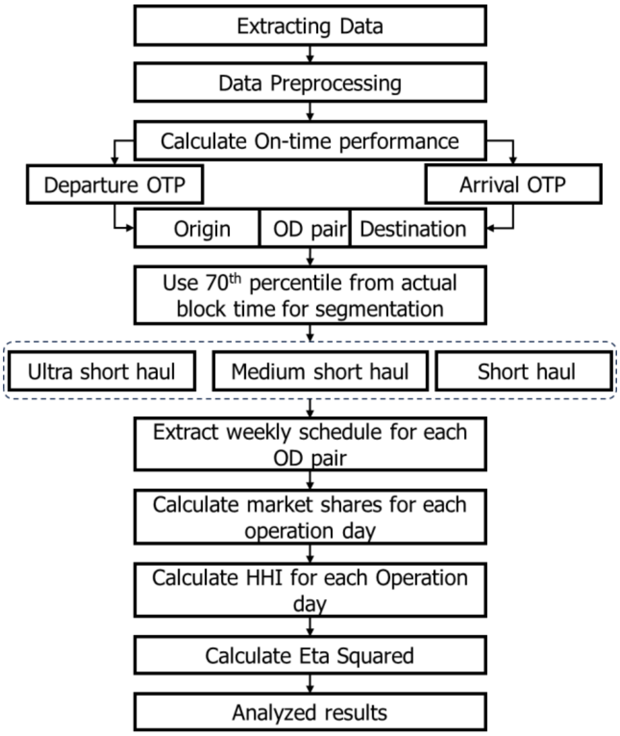

Figure 2. Research Flow

The methodology utilized in this study rigorously investigated the relationship between market concentration and on-time performance in the airline industry, explicitly focusing on departures and arrivals at large airports in the United States. The study sample includes all domestic flights aggregated by all sixty-three large airports in the US during the summer season (from April to September) in 2017. Still, we selected data only from April for the analysis. The study utilized two data sets published by the US Department of Transportation. In this analysis, we analyzed only 460,932 scheduled flight data to conclude. We excluded the non-schedule flights in the raw dataset.

As Figure 2 illustrates, this section outlines the sampling process, Airport category selection, Identification of different markets in the short-haul, Calculation of OTP, Calculation of Market Concentration, and Market Share Calculation. Finally, the study calculates the Eta-squares value between market concentration and on-time performance to observe the influence of market concentration on the on-time performance when the market moves from an oligopoly market to a duopoly market or vice versa.

3.1. DATA SOURCES & DESCRIPTION

The study utilized two data sources as primary data sources, published by the US Department of Transportation (DOT). The first data source is the Airline On-Time performance dataset, which contains scheduled and unscheduled domestic flight operational data. The second database provides details about airports.

3.2. SAMPLING PROCESS

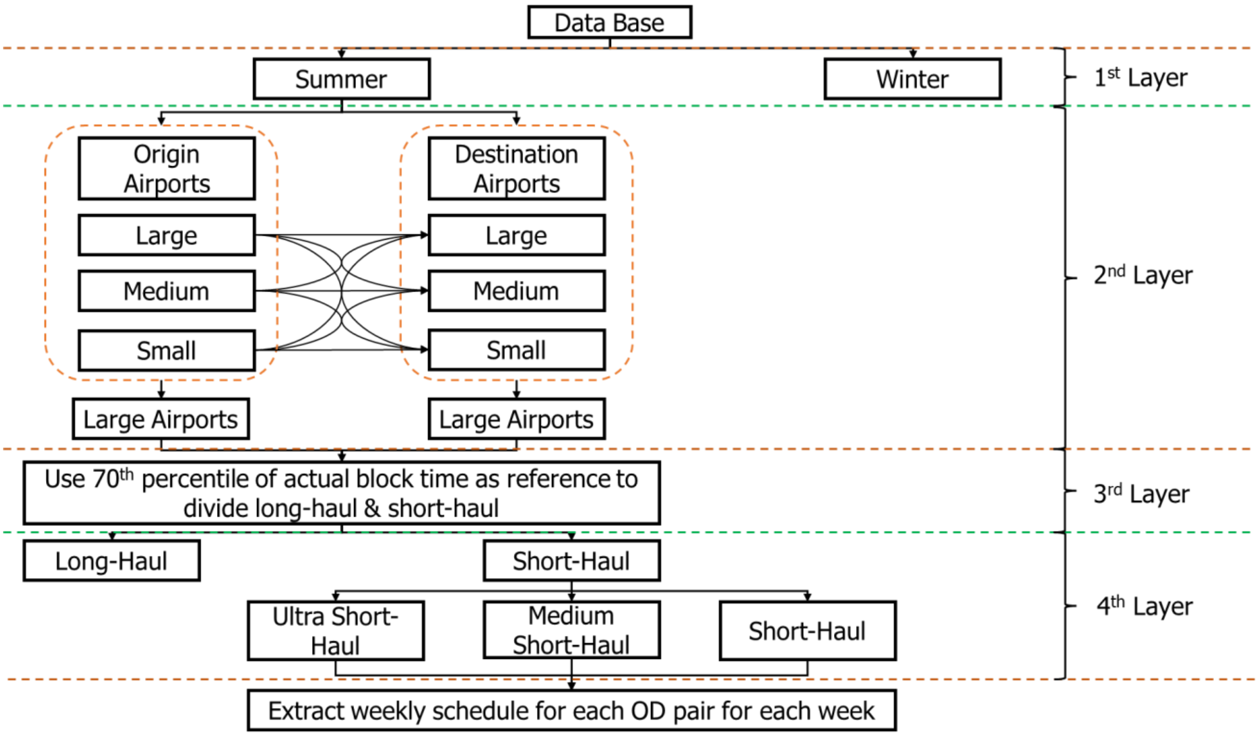

Figure 3. Sampling Process

Many factors impact the on-time performance. The main objective of this study is to identify how market concentration influences an airline's on-time performance. Therefore, we use a detailed sampling method, as presented in Figure 3, to eliminate other factors as much as possible.

The sample selection method is a crucial aspect of studying on-time performance (OTP) and market dynamics in the airline industry due to its high sensitivity to external factors. Studies have adopted various approaches to select airports for analysis, each tailored to their specific research objectives. In our paper, we focused on selecting a sample to ensure consistency and comprehensively analyze the impact of market concentration on OTP. This approach contrasts with and complements the methodologies utilized in other significant studies.

For instance, Mazzo-2003 analyzed data from US domestic flights by major carriers from 1988 to 2000, covering 250 airports and over 66 million flights (Mazzeo, 2003). This extensive data set aimed to capture a broad spectrum of market conditions and their impact on service quality and OTP. Here, the authors did not consider airport size or trip type (long haul, short haul), and the study analyzed data without separating summer and winter while introducing season as a parameter. The Zhang and Zhang-2006 approach selected the 25 most delayed airports in 1999 to identify "airport capacity and congestion when carriers have market power" (Zhang & Zhang, 2006). The approach in this case is somewhat narrowed down, but still, it does not consider the airport size. The traffic management strategy changes with the airport size. Therefore, in this case, the impact of airport traffic management may not be fully captured. Similarly, Vinayak Deshpande (Deshpande & Arikan, 2012) utilized OTP data between 2005 and 2007 without considering seasonal effects and the level of airport size, as previous studies mentioned. Lastly, (Bubalo & Gaggero, 2015) analyzed 3.5 million flights scheduled among 100 European airports with the same issue, without considering the season or the airport level.

Based on the literature mentioned above, (Mazzeo, 2003) found that additional competition positively correlates with OTP, which aids airlines in gaining market share. The authors concluded that a monopolistic market illustrates OTP. The findings of (Deshpande & Arikan, 2012) align with Mazzeo's findings.

On the other hand, some studies argue that competition worsens OTP, and markets with less competition illustrate high OTP (Rupp, Owens, & Plumly, 2006) (rince & Simon, 2014). These literature findings confirm a correlation between market share and on-time performance, as discussed in (Cheng-LungWu, 2010).

An airline has two seasons to publish its schedules (Ionescu, Gwiggner, & Kliewer, 2015). The summer season starts on the last Sunday of March and ends on the last Sunday of October. Winter begins on the last Sunday of October and finishes on the last Sunday of March (IATA). In (Mazzeo, 2003) study, January, April, and July were used for analysis, leading to some controversial results. The study produces unreliable coefficients for weather variables due to this selection. Typically, weather causes a maximum of 2% delay annually. Hence, we decided to control the weather factor while attempting to understand the effect of market concentration on OTP.

The study first selects summer to reduce uncertainties occurring due to weather conditions. Figure 4 shows that April in summer has comparatively average weather effects on on-time performance. Based on this observation, we selected April as the subject month for the analysis. We used a weekly schedule to analyze each operation date scheduled for flights and identified Monday (D1) as the first operation date of the week, and the rest followed the flow.

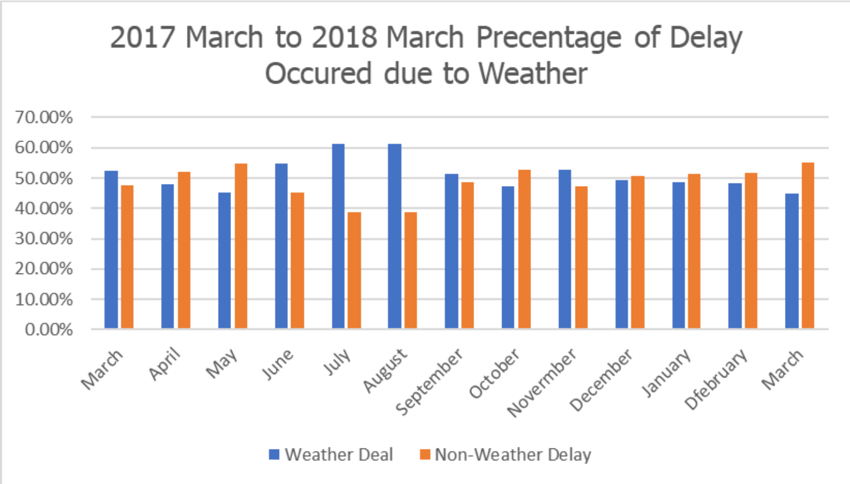

Figure 4. Delay percentage of 2017 March to 2018 March due to weather conditions and non-weather conditions

3.3.AIRPORT SELECTION

Table I. FAA Airport Category

Statutory Definition	Criteria
Large Hub	Handle one percent or more than one percent of commercial passengers per year
Medium Hub	Handle 0.25 to 1 percent of commercial passengers per year
Small Hub	Handle 0.05 to 0.25 percent of commercial passengers per year
Non-Hub	Handle less than 0.05 percent but more than 10,000 annual commercial passengers

Selecting airports for this research was challenging. Hence, the study employed the categorizing method developed by the FAA (Federal Aviation Authority) based on annual passenger movement, as shown in Table I (FAA, 2020). The first study ignores the non-hub category among the four airport categories due to the fewer enplanements. When considering the other three categories, the study identified nine Permutations (P(3,1)*P(3,1)) as shown in Figure 3 in the second layer (Hao & Hansen, 2013). The study assumed that the operation strategies of same-size airports are the same.

Based on that assumption, only three combinations were valid for the study, i.e., Large to Large, Medium to Medium, and Small to Small. Considering this study's number of movements and operational complexity, we consider OD pairs, which are Large to Large permutations. Before proceeding with our analysis, we checked whether our assumption matches the Large to Large combination, which has analyzed the 2017 departure OTP distribution. We noted here that the mean of the Dep. OTP is 81.35% with a 3.7% standard deviation, and all large airports maintain over 70% efficiency. With the descriptive value, we could assume that consistency prevails between the operational strategies of all large airports.

3.4. IDENTIFICATION OF DIFFERENT MARKETS IN REGULAR SHORT-HAUL

Air transportation has two main trip patterns, as explained in Table II, which explains the characteristics of these two markets (Sebastian Birolini, 2020). Among these two, the study chose the short-haul market for the analysis due to the market diversity. In a further study, a high percentage of airlines utilized narrow-body aircraft such as the Boeing 737 series or Airbus 320 series for short-haul markets due to low operation costs and faster turnaround times. Still, narrow-body aircraft have some weaknesses. The first weakness is the low range and capacity restriction.

Table II. Characteristics of short and long-haul flights

Criteria	Regular Short-Haul	Long-Haul
Aircrafts	Narrow & Wide Body	Wide Body
Schedule Block Time (SBT)	0 Hr < SBT < 6 Hrs	SBT > 6 Hrs
Distance	Less than 3000 Km	More than 3000 Km

The study identified that airlines use frequency strategies to overcome narrow body capacity constraints and lower the cost of passenger uplift. Therefore, the study determined that regular short-haul market frequency is a key factor in becoming a dominant competitor in a particular market.

Since this short-haul market shows significant complexity, we divided it into three subcategories in Table III. The objective of this segmentation is to obtain sharp results. The segmentation of the database study occupied the percentile method, commonly used within carriers to set SBT (schedule block time) (Hao & Hansen, 2013). In the subcategorizing method study, we used actual block time (ABT) instead of scheduled block time because of airport slot-related complications. It constantly fluctuates in ABT, so we use the 70th percentile (Hao & Hansen, 2013) of each OD pair for the clustering process (Table III).

Table III. Regular short-haul subcategories

Short-haul Subcategory	ABT duration	Value of ‘a’
Ultra Short-haul	0<ABT⩽120	1.7
Medium Short-haul	120<ABT⩽ 240	1.5
Short-haul	240<ABT⩽ 360	1.3

3.5. CALCULATION OF ON-TIME PERFORMANCE (OTP)

$$\text{On\_Time Performance} = \frac{\text{Number of Flights Operate On\_Time}}{\text{Total Number of flights operate}} \text{x}100\%$$

Equation 2. On-time performance calculation

As described, if a flight operates under the fifteen-minute rule (ICAO, 2017), it is considered an on-time flight. Flights operating outside the fifteen boundaries are considered as flights without on-time performance. As shown in Table IV, flight DL23 departure from PNS at 0920 falls into the departure time bulk of 0900–0959 and arrives at ATL at 1130, falling into the arrival time bulk of 1100–1159.

Then, by using Equation 2, we calculate the OTP for flight DL23; for the study, we used that value for all DL23 that depart in the 0900–0959 departure time bulk. As explained, the study utilizes the mentioned method to calculate departure and arrival on-time performance for all OD pairs.

Table IV. Example flight details

Flight number	Origin	Departure time bulk	Departure time	Destination	Arrival time bulk	Arrival time
DL23	PNS	0900-0959	0920	ATL	1100-1159	1130
DL43	SLC	2200-2259	2216	PSC	2200-2259	2255

3.6. CALCULATION OF MARKET CONCENTRATION

Market concentration is the "degree to which a limited number of companies control a significant portion of a market" (Press, 2023). This means the function of market share that each company holds in the same market, as illustrated in Equation 1. Calculation may not be possible without knowing the market share of each airline, as illustrated in Figure 2. After extracting the weekly schedule for each week and each OD-pair, we first calculate the market share for each carrier for the selected OD-pair as flowchart concentration can be explained: "the degree to which a limited number of companies control a significant portion of a market" (Press, 2023) which means its function of market share that each company holds in the same market as illustrated in Equation 1. Calculation may not be able to be undertaken without knowing the market share of each airline, as illustrated in Figure 2. After extracting the weekly schedule for each week and each OD-pair, we first calculate the market share for each carrier for the selected OD-pair as follows.

3.7. MARKET SHARE

Market shares depend on how much an airline influences its market and makes people willing to pay for its service. The degree of success rate of influence will be reflected in the percentage of market share that airlines gather. Airlines can influence customers based on three factors (Peter Belobaba, 2016), as mentioned below:

- Operating frequency
- Ticket fares relative to competitors
- Quality of the service

Two main models calculate market share based on the factors mentioned above: the first is the frequency share model (S-curve model), and the second is the quality of service index model. Since we consider only short-haul flights in this study, the study employed a frequency share model as shown in, where "MS(i)" is the market share of "ith" airline and "FS" frequencies of the subjected market. "n" is the number of airlines that operate in the subject OD market. "a" is an exponent, which always has more than one. As mentioned in Table III, the study used predetermined values for the exponent based on scheduled block time.

$$MS(i) = \frac{FS(i)^a}{\sum_{i=1}^{n} FS(i)^a}$$

Equation 3. Frequency Share Model/S-Curve Model

The s-curve (frequency share) model can be employed where 'frequency' is the key parameter of changing market share. This means airlines with higher frequencies tend to capture a more significant market portion. Therefore, this relationship is generally stronger in short-haul markets, i.e., trips less than 6 hours of block time. Since this study focuses on short-haul markets, the frequency share model can be used for market share calculations. The exponent value typically varies between 1.3 and 1.7. As we divided the short-haul market into three sub-markets, we allocated the exponent value as 1.7 to Ultra short-haul, 1.5 to Medium short-haul, and 1.3 to regular short-haul.

(SBT) or distance between OD, as explained in Table III: Characteristics of Short and Long-Haul Flights (Sebastian Birolini, 2020). Among these two, the study selects the short-haul flight operation for analysis because it is highly sensitive to time. From the passenger viewpoint, passengers prefer shorter schedule block time (Lei Kang, 2017) because it offers less travel time. Most airlines use narrow-body aircraft (e.g., Boeing 737 family or Airbus 320 family) for operation due to their lower operation costs. Still, capacity restrictions may occur due to the narrow-body aircraft's seat configuration. Hence, we believe that a future study must develop a robust method to calculate more accurate exponent values for each market because each market is different.

The airlines use frequency strategies to overcome narrow body capacity constraints and lower the cost of passenger uplift. We identified that with an increase in schedule block time as strategy to gain market share. Because of that in this study, we divide short-haul flights into three subcategories, as shown in Table III: Short-Haul Subcategories, to illustrate accurate results. In the subcategorizing method study, we used actual block time (ABT) instead of scheduled block time because of airport slot-related complications SBT can be deviate from ABT. Even ABT also constantly fluctuates; hence, we use the 70th percentile of each OD pair for the clustering process, as shown in Table III: Short-Haul Subcategories.

3.8. CALCULATING ETA-SQUARED (η^2)

Eta squared is a method to measure the association between independent and predictor variables. Eta squares measure the proportion of variance associated with predictor variables maintained with independent variables (Adams M.A, 2014). Market concentration Equation 1 is not a linear function. In a non-linear relationship, Pearson's r correlation will not provide accurate results to understand how market concentration affects on-time performance. The study utilized Eta squared for the calculation to mitigate this issue. Eta squared can be calculated using Equation 4, where the SS_{effect} is the sum of squares of effects for one variable and SS_{total} is the total sum of squares.

$$\eta^2 = \frac{SS_{effect}}{SS_{total}}$$

Equation 4. Eta Squared calculation

The value of Eta squares varies between 1 and 0; if the values closer to 1 reflect a higher proportion of variance of the predictor variable, it can be explained by an independent variable or variables. The Eta squared does not have a specific guideline for interpreting results. Therefore, the study follows Table V (National University Academic Success center, 2023).

Table V. Guideline for interpretation

Eta Squared	Effect Size
$0 \leq \eta^2 \leq 0.06$	Small effect size
$0.06 < \eta^2 \leq 0.14$	Medium effect size
$0.14 < \eta^2 \leq 1$	Large effect size

3.9. HYPOTHESIS

As explained in the introduction, the main objective of this study is to understand the behavior of OTP concerning changes in corresponding market concentration. However, we must first check whether or not the impact of market concentration on OTP is significant. We analyzed this behavior by using the following hypothesis:

- H_0 = The punctuality of scheduled flight services is internally independent of the level of airline market concentration in markets where flight frequency is a pivotal factor in acquiring market dominance.
- H_1 = The punctuality of scheduled flight services is not internally independent of the level of airline market concentration in markets where flight frequency is a pivotal factor in acquiring market dominance.

4. RESULTS & DISCUSSION

We intend to discuss the results of the study in this section. As Table II illustrates, the study discovered interesting facts on how competition for short-range trips shapes the carrier's on-time performance. The section contains four main areas, which are subcategories. Table III of the short-haul market, as Figure 1 illustrates, shows that airlines lost 6.72% of their on-time performance due to issues they could control. Nevertheless, from an airline's perspective, they could not control most things because every carrier does their best to increase their market share. In this case, the competition will not be at equilibrium for a long period because the carrier with the competitive edge will gain the market share. The increase in market share means the market is becoming more concentrated on the carrier. The study tries to apply its hypothesis here because on-time performance is one of the most critical KPIs in the aviation industry. Hence, understanding how market concentration affects is vital. In the discussion, first, we debated the result of Eta squared and then used the kernel density function to analyze the behavior of OTP when market concentration changed.

4.1. ETA SQUARED RESULTS

Table VI. Eta Squared Results

Operation Day	Eta Squared value					
	Ultra Short-haul Market		Medium Short-haul		Short-haul	
	DEP	ARR	DEP	ARR	DEP	ARR
1	0.477002	0.49425	0.33471	0.3257	0.53337	0.49436
2	0.453839	0.47088	0.32073	0.29593	0.54344	0.52925
3	0.442793	0.459	0.33643	0.32266	0.4919	0.46874
4	0.434547	0.45125	0.28895	0.29303	0.49067	0.49855
5	0.457466	0.46953	0.30027	0.30276	0.44521	0.45152
6	0.46462	0.4986	0.28564	0.29362	0.46279	0.43979
7	0.480299	0.48961	0.28574	0.28249	0.4715	0.45211

Before further analysis, we checked for any effects and the intensity of the effects based on Table V. The study utilized Eta squared to measure the impact of arrival on-time performance (ARR_OTP_OD) and departure on-time performance (DEP_OTP_OD) for the subjected OD pair by market concentration. The analysis has been run for each short-haul sector for each operation day. The results illustrated in Table VI confirm that concentration can generate a significant effect on OTP in all short-haul markets. The outcomes of Eta square revealed that market concentration can considerably impact each market segment in short-range air travel. Based on the Table VI values, the effect of market concentration on OTP is significant except in medium- and short-haul markets. This scenario can result from our assumption about the value of the exponent of the S-curve function.

As shown in Table III, the study assumes the value of the exponent based on scheduled block time. However, the Eta squared results indicate that the effects of market concentration over 0.4 in ultra-short and short-haul segments mean that in these segments, concentration can explain over 40% of OTP variation, though it is less than 34% in medium-short-haul (For all related tables and figures, please refer to Appendices A, B, and C for statistical evidence).

4.2. ULTRA SHORT-HAUL

According to Figure 6, departure on-time performance and arrival on-time performance have similar distributions. Hence, we can conclude the presence of minimum external influences on flight operation. As illustrated in Figure 5, each operation day has a nearly similar market distribution. Due to this similarity, we extracted the generalized density function, Figure 6, for all three parameters. Figure 6 illustrates the market concentration of this ultra short-haul market, with a minimum value of 0.216, clearly explaining that this market has only moderately and highly concentrated markets.

Among these two markets, the percentage of the moderately concentrated market is less than 25%. The majority of ultra short-haul markets are highly concentrated, meaning most of these markets are duopoly or monopoly. Less than five carriers will dominate the market if they are an oligopoly. In this case, the market is starting to reach its peak "monopoly" at the 75th percentile, and the remaining 25% are monopoly markets.

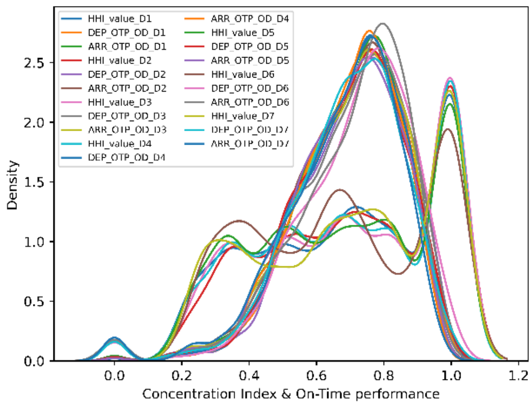

Figure 5. HHI & OTP comparison of all operation day ultra-short

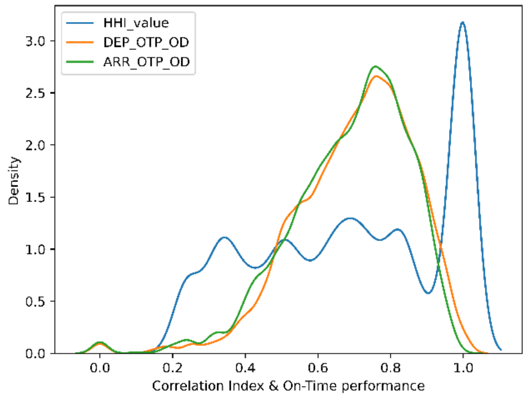

Figure 6. Generalized Density Functions of HHI & OTP for all operation days ultra-short

4.2.1. MODERATELY CONCENTRATED ULTRA SHORT-HAUL MARKETS

Next, the study used HHI conditions (Bromberg, 2023) to re-cluster the ultra short-haul market. We used the $0.15 \leq HHI < 0.25$ condition to filter out moderately concentrated markets from ultra short-haul. Figure 7 illustrates the same scenario as Figure 5, and Figure 8 illustrates the same scenario as Figure 6, but within the mentioned HHI limit. We noted a significant difference in OTP distribution between D6 (Saturday) and the rest in Figure 8. The mean value of D6 is 0.82 (ARR) and 0.81 (DEP), which illustrates good OTP, but the average mean values of the rest of the operation days are 0.523 (ARR) and 0.58 (DEP).

The next question is why the OTP of D6 improved the way it occurred. We did some frequency analysis to answer that question, as shown in Figure 10. With Figure 10, we recognized that the low frequency of D6 may cause a significant improvement in OTP. However, this D6 improvement could not significantly impact generalized distribution. Figure 9 shows the low frequency of D6, allowing us to ignore the difference.

Figure 7 shows the unique behavior of OTP in this market. The characteristic of this market is that several carriers hold significant market share, but only a few. Each carrier has some degree of market power in this situation, and there can be more product diversification. This indicates product innovations and a somewhat easy market for newcomers to enter. Due to this continued competition to gain more market share, new carriers may cause operational inefficiencies, as illustrated in Figure 7.

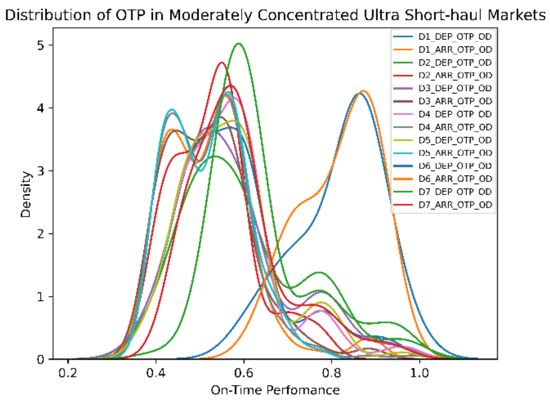

Figure 7. OTP Distribution for each Operation Day in Moderately Concentrated Ultra Short-Haul Markets

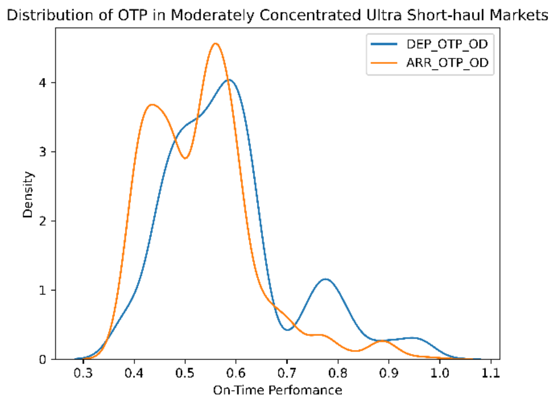

Figure 8. Generalized OTP Distribution for Moderately Concentrated Ultra Short-Haul Markets

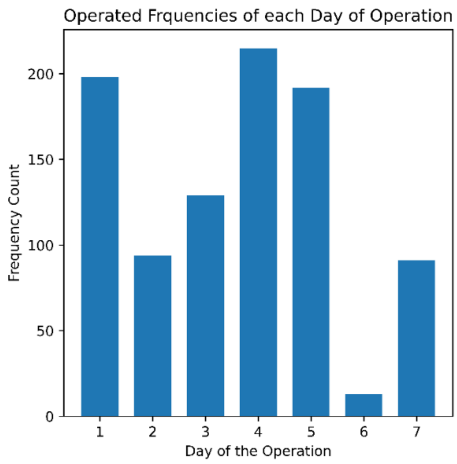

Figure 9. Frequency Analysis of Each Operation Day of Moderately Concentrated Ultra Short-Haul Market

4.2.2. HIGHLY CONCENTRATED ULTRA SHORT-HAUL MARKETS

Figures 11 and 12 follow the same scenarios as Figures 7 and 8. When the market becomes highly concentrated, it becomes dominant by very few carriers. The common structure of a highly concentrated market is a duopoly or monopoly, so the most noticeable thing is imperfect competition. Comparing Figures 7 and 10 signifies the competition reductions because, in Figure 11, uniformity increases within OTP density functions for each operation day. Since carriers of highly concentrated markets hold high market power, they can maintain OTP at certain levels without losing market share. In this study, the subject market has a mean departure OTP of 0.71 and a mean arrival OTP of 0.7. The OTP of this market is neither highly efficient nor highly inefficient.

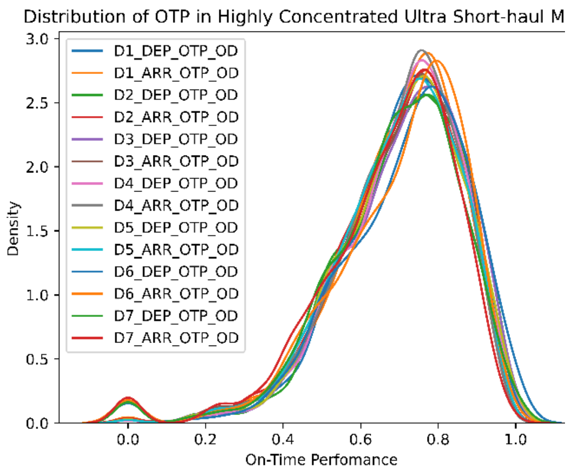

Figure 10. OTP Distribution for each Operation Day in Highly Concentrated Ultra Short-Haul Markets

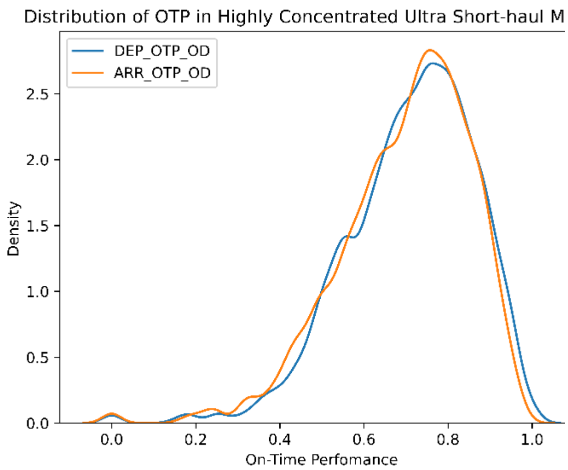

Figure 11. Generalized OTP Distribution for Highly Concentrated Ultra Short-Haul Markets

4.3. MEDIUM SHORT-HAUL

4.3.1. MODERATELY CONCENTRATED MEDIUM SHORT-HAUL MARKETS

Moderately concentrated medium short-haul market OTP behavior significantly differs from moderately concentrated ultra short-haul market. As illustrated in Figure 12, D7 operations do not exist in this market because all D7 operations are in highly concentrated markets. According to the generalized density function illustrated in Figure 13, with 0.81 of the mean arrival OTP and 0.79 of the mean departure OTP, those values indicate that the market is keeping good OTP. However, only on some operation days, for example, for D5 departure OTP, the shape of the density function shows that the OTP of Day 5 is not so good, with a flatter distribution. Still, generally, arrival-on-time performance is better than departure OTP.

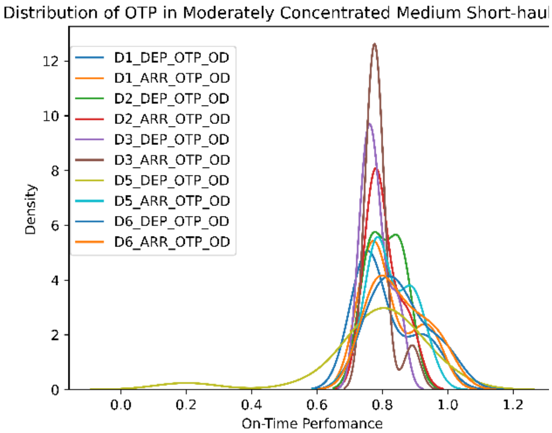

Figure 12. OTP Distribution for each Operation Day in Moderately Concentrated Medium Short-Haul Markets

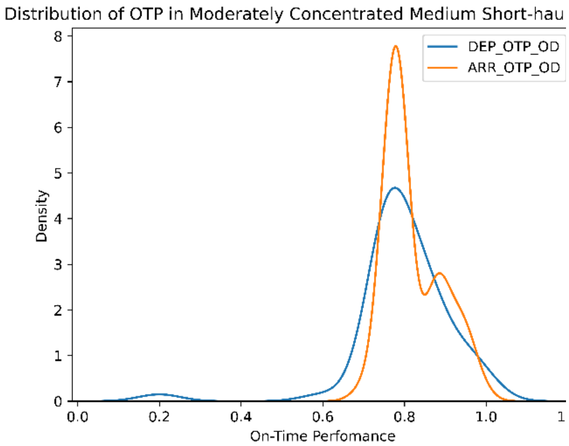

Figure 13.Generalized OTP Distribution for Moderately Concentrated Medium Short-Haul Markets

4.3.2. HIGHLY CONCENTRATED MEDIUM SHORT-HAUL MARKETS

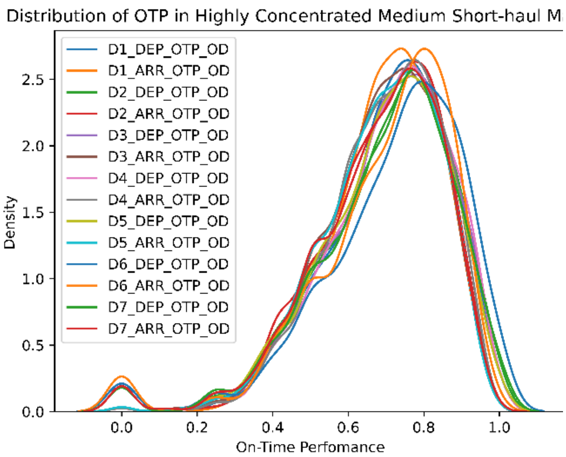

Figure 14. OTP Distribution for each Operation Day in Highly Concentrated Medium Short-Haul Markets

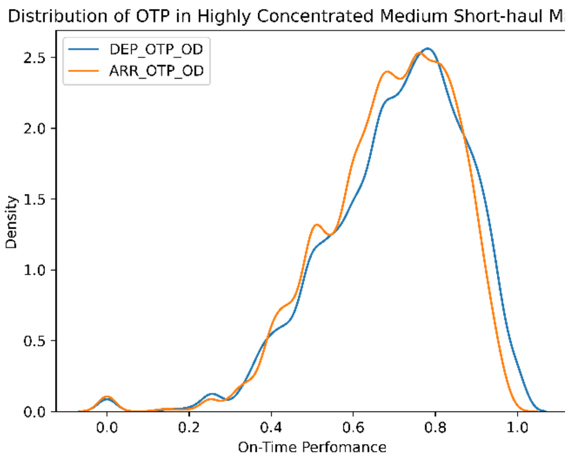

Figure 15. Generalized OTP Distribution for Highly Concentrated Moderately Short-Haul Markets

As illustrated in Figure 14 and Figure 15, the highly concentrated medium short-haul market also demonstrates similar characteristics to the highly concentrated ultra short-haul market. Unlike the ultra short-haul market, when concentration shifts from moderate to high in this medium short-haul market, mean OTP decreases from arrival and departure sectors. On arrival, OTP decreased from 0.81 to 0.68, and departure from 0.79 to 0.70. This phenomenon explains the reduction of competition when the market becomes highly concentrated.

4.4. REGULAR SHORT-HAUL

4.4.1. MODERATELY CONCENTRATED SHORT-HAUL MARKETS

Figures 16 and 17 illustrate OTP behavior in a moderately concentrated short-haul market. In the common behavior of medium and short, the density around the mean is higher in the arrival density function than in departure. This is obvious when comparing the standard deviations of functions. It means airlines are more concerned about arrival time than departure time because customers select departure time based on their preferred arrival time (Lu Hao, 2014). The mentioned consumer behavior leads airlines to introduce a longer schedule block time with buffer time than is actually required to ensure the OTP, which increases the operation costs. The carrier that achieves the highest arrival OTP with the minimum cost can gain market share. High competitiveness is the nature of moderately concentrated markets, represented in Figure 16.

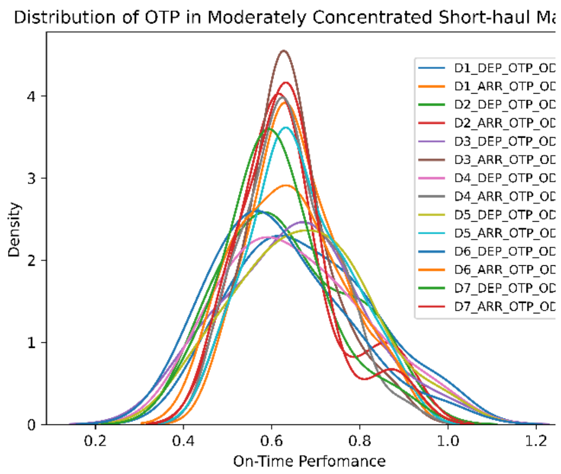

Figure 16. OTP Distribution for each Operation Day in Moderately Concentrated Short-Haul Markets

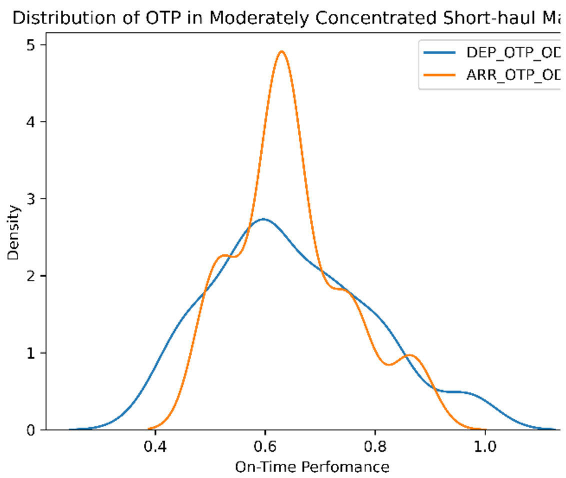

Figure 17. Generalized OTP Distribution for Moderately Concentrated Short-Haul Markets

4.4.2. HIGHLY CONCENTRATED SHORT-HAUL MARKETS

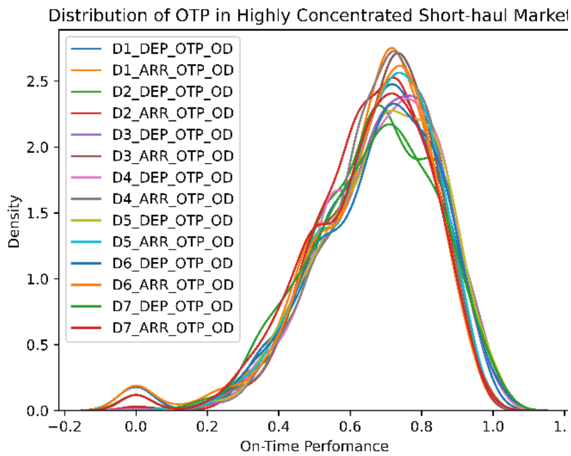

Figure 18. OTP Distribution for each Operation Day in Highly Concentrated Short-Haul Markets

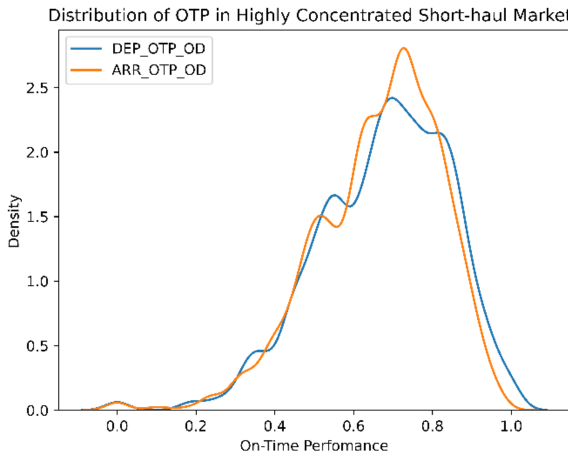

Figure 19. Generalized OTP Distribution for Highly Concentrated Short-Haul Markets

Highly concentrated markets throughout all segments illustrate the same level of service. Figure 18 shows that the density function of OTP for all operation days is more or less the same as in Figures 10 and 14. Figure 19 illustrates that arrival OTP 0.66 and departure OTP 0.67 are nearly identical to other segments. It explains that if any short-haul market gets more and more concentrated, there is a risk of losing OTP in the market.

5. CONCLUSION

The study's findings highlight the importance of sampling in understanding market competition in the aviation market. The research used a sampling method based on industry standards and added two extra layers to improve generalizability. The findings suggest that focusing on a diverse range of airports or locations is essential for a comprehensive understanding of market dynamics and making informed decisions based on reliable data. This approach ensures a more accurate representation of market dynamics and enhances the generalizability of the findings.

By dividing short-haul flights into three groups, we can understand how competition varies in different markets, even with the same level of market concentration. However, in every market condition, reject the null hypothesis.

The study suggests that to gain market share, each market must approach it with slightly different strategies. For example, the most competitive market for all three short-haul segments is moderately concentrated. Every carrier attempts to become a market leader by gaining market share, so the level of competition in each segment is different. In highly concentrated markets, all three market segments show the same level of OTP because of low competition.

In the ultra short-haul market, it helps to understand unexpected cases because D6 OTP shows a higher mean value than the rest. It helps to understand that a decrease in frequency leads to an increase in OTP. This issue requires further investigation.

The study helps both the main stakeholders' airlines and airport operators. Airlines can use the study results as follows:

Airline can deliberately utilize these insights to modify flight frequency to gain more market share and become a market leader, especially in markets with moderate concentration. However, if the market fails to demonstrate satisfactory operational performance, airport operators can use this type of study to determine the level of competition in that particular market. If the market becomes monopoly-level, the carriers will not care about the OTP based on results due to a lack of competition and high negotiation power. Similarly, it is crucial for airport operators to comprehend the reasons behind the carriers' underperformance. Studies suggest that if the underperformance of airlines is due to a lack of competition, airport operators can modify their policies to compel carriers to increase their OTP, thereby enhancing passenger satisfaction. But before implementing new policies, operators need to understand why and how competition changes to a certain level because there can be several factors that cause a market to reach a certain level.

In conclusion, market concentration needs more detailed analysis to understand its impact at the microlevel. Market concentration influences other uncertain factors to reach a certain operational efficiency level.

We can recommend several improvements to this study. First, since market concentration significantly affects every short-haul market, it is a critical factor in modeling OTP. However, since the mathematical function of market concentration does not provide linear values, we may not be able to utilize the linear technique to model OTP. The second recommendation is that further studies are necessary to determine the exponent value of the s-curve function, which will help to increase this study’s accuracy. We think future studies need to look to improve the s-curve function to capture more complex parameters such as pricing strategies, connectivity, consumer preference, et cetera. The final recommendation is that it would be better to expand this study to all origin-destination combinations in order to build a more sophisticated decision support system.

Market concentration is a widely used measure to assess the level of competition within an industry. By examining the market share of a few dominant firms, it provides insights into the competitive dynamics and potential barriers to entry. However, as mentioned, it is important to consider other factors, such as pricing strategies, product differentiation, and consumer preferences, to comprehensively understand how competition influences and shapes the market.

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APPENDIX

APPENDIX A. ETA SQUARED RESULTS FOR ULTRA SHORT-HAUL SEGMENT

Operation Day	Source	SS	DF	MS	F	p-unc	Eta Square
1	ARR_OTP_OD	108.704992	450	0.241567	6.347734	1.33E-216	0.494245
	HHI Value	111.236444	2923	0.038056	-	-	-
	DEP_OTP_OD	104.912467	439	0.238981	6.095586	4.60E-203	0.477002
	HHI Value	115.028969	2934	0.039206	-	-	-
2	ARR_OTP_OD	71.790466	430	0.166955	4.217898	1.04E-106	0.470882
	HHI Value	80.668962	2038	0.039582	-	-	-
	DEP_OTP_OD	69.192027	409	0.169174	4.183253	1.66E-102	0.453839
	HHI Value	83.2674	2059	0.040441	-	-	-
3	ARR_OTP_OD	87.674534	453	0.193542	4.667354	3.75E-137	0.459003
	HHI Value	103.33621	2492	0.041467	-	-	-
	DEP_OTP_OD	84.578199	436	0.193987	4.572968	3.11E-130	0.442793
	HHI Value	106.432545	2509	0.04242	-	-	-
4	ARR_OTP_OD	120.902114	464	0.260565	6.475735	2.56E-244	0.451248
	HHI Value	147.026415	3654	0.040237	-	-	-
	DEP_OTP_OD	116.427537	452	0.257583	6.232959	4.78E-229	0.434547

	HHI Value	151.500992	3666	0.041326	-	-	-
5	ARR_OTP_OD	104.660377	467	0.224112	5.551516	2.42E-187	0.469534
	HHI Value	118.242377	2929	0.04037	-	-	-
	DEP_OTP_OD	101.970349	450	0.226601	5.520157	6.70E-182	0.457466
	HHI Value	120.932406	2946	0.04105	-	-	-
6	ARR_OTP_OD	67.292009	397	0.169501	4.263124	1.26E-96	0.498595
	HHI Value	67.671303	1702	0.03976	-	-	-
	DEP_OTP_OD	62.706648	387	0.162033	3.839092	2.51E-81	0.46462
	HHI Value	72.256664	1712	0.042206	-	-	-
7	ARR_OTP_OD	109.351258	426	0.256693	6.642935	8.57E-222	0.48961
	HHI Value	113.99247	2950	0.038642	-	-	-
	DEP_OTP_OD	107.271868	410	0.261639	6.685689	1.62E-218	0.480299
	HHI Value	116.07186	2966	0.039134	-	-	-

APPENDIX B. ETA SQUARED RESULTS FOR THE MEDIUM SHORT-HAUL SEGMENT

Operation Day	Source	SS	DF	MS	F	p-unc	Eta Square
1	ARR_OTP_OD	63.4302	459	0.13819	3.53583	2.63E-97	0.3257
	HHI Value	131.32	3360	0.03908	-	-	-
	DEP_OTP_OD	65.1848	478	0.13637	3.51646	4.05E-99	0.33471
	HHI Value	129.565	3341	0.03878	-	-	-
2	ARR_OTP_OD	49.2455	453	0.10871	2.74084	2.81E-57	0.295929
	HHI Value	117.164	2954	0.03966	-	-	-
	DEP_OTP_OD	53.3719	476	0.11213	2.90735	6.33E-67	0.320726
	HHI Value	113.038	2931	0.03857	-	-	-
3	ARR_OTP_OD	60.2853	459	0.13134	3.21526	2.62E-80	0.322664
	HHI Value	126.551	3098	0.04085	-	-	-
	DEP_OTP_OD	62.8579	475	0.13233	3.28969	9.08E-86	0.336434
	HHI Value	123.978	3082	0.04023	-	-	-
4	ARR_OTP_OD	67.7444	479	0.14143	3.55905	1.76E-106	0.29303
	HHI Value	163.442	4113	0.03974	-	-	-
	DEP_OTP_OD	66.802	478	0.13975	3.49757	4.58E-103	0.288953
	HHI Value	164.384	4114	0.03996	-	-	-
5	ARR_OTP_OD	53.9454	459	0.11753	2.98562	5.97E-70	0.302757
	HHI Value	124.235	3156	0.03937	-	-	-
	DEP_OTP_OD	53.5022	473	0.11311	2.85053	4.49E-65	0.30027
	HHI Value	124.678	3142	0.03968	-	-	-
6	ARR_OTP_OD	49.5516	415	0.1194	2.62723	9.52E-48	0.29362
	HHI Value	119.209	2623	0.04545	-	-	-
	DEP_OTP_OD	48.205	422	0.11423	2.47873	2.09E-42	0.285641
	HHI Value	120.556	2616	0.04608	-	-	-

7	ARR_OTP_OD	62.0498	442	0.14038	3.50688	1.22E-96	0.282491
	HHI Value	157.602	3937	0.04003	-	-	-
	DEP_OTP_OD	62.7642	461	0.13615	3.40006	2.86E-94	0.285744
	HHI Value	156.888	3918	0.04004	-	-	-

APPENDIX C. ETA SQUARED RESULTS FOR THE SHORT-HAUL SEGMENT

Operation Day	Source	SS	DF	MS	F	p-unc	Eta Square
1	ARR_OTP_OD	25.9705	219	0.11859	3.98229	2.34E-45	0.533368
	HHI Value	22.721	763	0.02978	-	-	-
	DEP_OTP_OD	24.0712	225	0.10698	3.28941	5.05E-34	0.494362
	HHI Value	24.6203	757	0.03252	-	-	-
2	ARR_OTP_OD	20.4853	202	0.10141	2.99344	2.46E-23	0.543443
	HHI Value	17.2101	508	0.03388	-	-	-
	DEP_OTP_OD	19.9503	197	0.10127	2.92769	2.94E-22	0.529252
	HHI Value	17.745	513	0.03459	-	-	-
3	ARR_OTP_OD	19.498	213	0.09154	2.6316	6.03E-20	0.491896
	HHI Value	20.1405	579	0.03479	-	-	-
	DEP_OTP_OD	18.5802	202	0.09198	2.57708	9.74E-19	0.468741
	HHI Value	21.0583	590	0.03569	-	-	-
4	ARR_OTP_OD	30.3681	234	0.12978	3.78348	7.15E-47	0.490671
	HHI Value	31.5229	919	0.0343	-	-	-
	DEP_OTP_OD	30.8558	235	0.1313	3.8838	6.89E-49	0.498551
	HHI Value	31.0352	918	0.03381	-	-	-
5	ARR_OTP_OD	22.4148	224	0.10007	2.79441	1.24E-25	0.445214
	HHI Value	27.9314	780	0.03581	-	-	-
	DEP_OTP_OD	22.7324	219	0.1038	2.95083	4.54E-28	0.451522
	HHI Value	27.6138	785	0.03518	-	-	-
6	ARR_OTP_OD	19.3028	185	0.10434	2.92894	2.85E-23	0.462786
	HHI Value	22.4072	629	0.03562	-	-	-
	DEP_OTP_OD	18.3435	181	0.10135	2.74545	1.99E-20	0.439787
	HHI Value	23.3665	633	0.03691	-	-	-
7	ARR_OTP_OD	28.261	219	0.12905	3.64191	4.80E-42	0.471499
	HHI Value	31.6775	894	0.03543	-	-	-
	DEP_OTP_OD	27.0989	217	0.12488	3.40724	1.50E-37	0.452112
	HHI Value	32.8396	896	0.03665	-	-	-

AUTHORS' BIO

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