Revenue Characteristics of Long-Haul Low Cost Carriers in Southeast Asian market

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Abstract

This study is set out to investigate the revenue characteristics of long-haul low-cost carriers (LHLCCs) in the Southeast Asian market using a newly established metric that calculates *revenue / equivalent flight capacity / block hour* (REB). The study also investigates 1) how do LHLCCs yields compare to full-service network carriers (FSNCs)? 2) Are LHLCCs positively impacted by smaller share of connecting passengers? 3) Are LHLCCs positively impacted by ancillary revenues? 4) Do LHLCCs benefit from higher load factors and seat densities?

LHLCCs overall performed 26.6% less in overall REB compared to their FSNC counterpart despite LHLCCs generating 43.9% less yield. This is a result of less revenue diluting connecting passengers, higher average ancillary revenue per block hour, higher average load factors and higher average seat densities for LHLCCs. Furthermore, the findings unravelled were consistent with earlier REB research conducted on the North Atlantic market.

With regards to the LHLC model, a new light is shone with information from the southeast Asian market indicating that its performance has the potential to be comparable to FSNCs.

Keywords: Long-Haul Low-cost, Revenue characteristics, REB, Airline industry

1. Introduction

In many industries, competitors opt to take one of three strategies to achieve success against one another; cost leadership, focus, or differentiation (Porter, 1985). In the airline industry, the two most notable competing strategies are the cost leadership and differentiation strategies taken in the form of low-cost carriers and full service network carriers (FSNCs) respectively. Since their inception in the 1970's, low-cost carriers have shown their strength and dominance in the short-medium haul markets against FSNCs in most global markets. Notable examples include Southwest airlines, Ryanair, AirAsia, Azul and Indigo. Over the decades, low-cost carriers have expanded and saturated the short-medium haul markets with success. However, entrance of the low-cost model to long-haul markets has not been as easy. Many airlines in the past have failed implementing the long-haul low-cost carrier (LHLCC) model, while currently, a handful of airlines are operating the model but with uncertainty. The model does not guarantee success or profits, and therefore is yet to be proven.

The literature concerned with the LHLC model is small in quantity and unbalanced in research topics. With regards to the financial performance of LHLCs, studies deal with insight on cost reductions of the model (Francis et al., 2007; Morrell, 2008; Wensveen and Leick, 2009; Douglas, 2010; Moreira et al., 2011; Whyte and Lohmann, 2015) with more rigour whereby data for cost is sourced from reliable sources, while studies with insight on revenue generation (Tretheway, 2004; Francis et al., 2007; Morrell, 2008; Douglas, 2010; Daft and Albers, 2012; De Poret et al., 2015; Wilken et al., 2016) usually use their own empirical

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assumptions that vary from study to study. It was not until Soyk et al. (2018) who developed a metric that calculated the *revenue / equivalent flight capacity / block hour* (REB). This allowed the analysis of the commercial characteristics of airlines, creating a new branch in the literature to do with the data-driven revenue analytics of the LHLC model.

This paper aims to fill this gap in the LHLC literature by characterising the revenue characteristics of the Southeast Asian (SEA) market using the REB metric. The REB metric is the only metric that allows for the accurate comparison of revenue generation between FSNCs and LHLCCs of different aircraft types, seat densities, stage lengths and cabin configurations. This will be further explained in the methodology section. Therefore, it is seen as the most comprehensive metric to date to be used for such a study. We aim to discover how comparable the revenue performance of LHLCCs is to FSNCs across numerous city-pairs in the Southeast Asian region, and in doing so, answer the following research questions:

1. How do LHLCCs yields compare to FSNCs?
2. Are LHLCCs positively impacted by a smaller share of connecting passengers?
3. Are LHLCCs positively impacted by ancillary revenues?
4. Do LHLCCs have higher load factors and higher seat densities?

What is special about the Southeast Asian market is that it is home to two of the largest LHLCCs, AirAsiaX and Scoot ,with 13% and 7% of global long-haul low-cost scheduled seat capacity in 2019 respectively (OAG, 2021). In addition, their headquarters are 300 km away from each other, offering the opportunity to analyse two LHLCCs who are close to one another and offer flights to numerous destinations. This allows for the data set to be large and extensive, allowing for a reasonable comparison of FSNCs and LHLCCs.

The results will compliment Soyk et al. (2018)'s findings conducted on the North Atlantic market and help create a more cohesive analytical picture of the LHLC model.

The paper is structured as follows: Section 2 presents a review of previous revenue studies on the LHLC model. Section 3 consists of the methodology. There, all the logical and technical steps are explained in detail as well as their execution and the compromises done along the way. The results and discussion are presented in Section 4. Section 5 concludes the paper, outlines weaknesses, and proposes areas for further research.

2. Literature Review

This literature review will focus on data-driven studies on the cost characteristics, revenue characteristics and the profitability of the LHLC model. Data sources used in these studies and the geographical regions where the studies were conducted will be mentioned. This is to create a data-driven, and geographical understanding of academic focus.

2.1. LHLCCs data-driven studies

Francis et al. (2007) looks at revenue per passenger type, i.e. high-yield premium passengers and basic economy passengers, when evaluating the applicability of the cost advantages of the low-cost model onto long-haul flight. The study concludes that FSNCs are dependant on high yield First and Business class passengers, and often use the revenue generated to cross-subsidise economy seats to offer more attractive lower price tickets. This in turn competes more effectively with LHLCCs. In addition, the study compared the cost advantages of traditional low-cost carriers and found that LHLCC operations can be possible only in large markets where demand is high enough.

Morrell (2008) observes the cost advantages of an intra-European low-cost carrier and compares the cost advantages between short-haul and long-haul flight only to find that the advantages might not be as transferable onto long-haul routes. Their geographical focus was centred around the UK with destinations spanning from New York to non-EEA cities. The study also considered LHLCCs' dependency on large dense markets that can provide the carriers with enough feed traffic, and the subsequent competitive response from incumbent airline. Such factors resulted in doubt in the author's conclusion of the model.

In the 2010's, in-depth quantitative studies started to dig deeper into the long-haul low-cost model. Moreira et al. (2011) built a cost simulation based on the Boeing 767-300 and demonstrated that the cost advantages do not exceed 10% that of FSNCs. Daft and Albers (2012) conducted a route *profitability* analysis on LHLC flight scenarios and found that LHLC flight is possible if suitable trunk routes are identified and the service is unbundled, i.e. instead of an all-inclusive ticket, the flight experience is broken up and the passengers are prompted to pay for whichever service they need or want. For example, seat location, in-flight catering, blankets, in-flight entertainment, etc.

De Poret et al. (2015) assumed the lowest available advance-booking fare found in the competing FSNC across all passengers with a FSNC load factor of 80% and conducted a sensitivity analysis to determine the LHLCC models sensitivity to external factors such as fuel price, demand, and cargo revenue when operating the B787-8. With the bulk of their data sourced from Boeing, and their two routes analysed being London Gatwick-Los Angeles International and Manchester-Newark Liberty International, they discovered that fluctuations in demand are more detrimental on profitability than fluctuations in fuel price. When load factors are reduced to 60% (from the average 80-85%), and extra cargo revenue is accounted for (due to freed up space from less passengers)), a lower load factor was more damaging than increasing fuel prices.

In the history of aviation, long-haul flights were always full-service. The LHLC model aims to fly its passengers for 6-12 hours with comfort and amenities stripped off. The question of passenger willingness naturally arises. Jiang (2013) surveyed long-haul passengers in the South-East Asian/Pacific market. The survey revealed a different set of scenarios. Long-haul low-cost passengers prioritised assurance first (i.e. feeling safe when flying with an airline) and then satisfaction with the airfare when flying with LHLCCs like Jetstar and AirAsiaX. Separately, full-service network passengers first prioritised satisfaction with service and airline's flight schedule second. The study also found that expectations, which differ from one socia-cultural demographic to the other, play a large role in a passenger's sense of satisfaction with the airfare.

Hunt and Truong (2019) surveyed 1,412 passengers flying within the trans-Atlantic market on the factors that impacted their choice of LHLCCs and FSNCs. When *choosing between* LHLC carriers, the airfare impacted their choice first and comfort came second. When *choosing between* FSNCs, satisfaction from service came first and on-time flight scheduling impacted their choice second. When *loyalty* was investigated, passengers are more loyal to a FSNC that offers an all inclusive flight than a LHLCC with a no-frills service. When asked about *remaining or switching* from a FSNC or a LHLCC, a spectrum of answers emerged. Some FSNC passengers would only want to fly full-service, some would gladly switch to a LHLCC for a cheaper fare. Some LHLCC passengers would gladly continue flying with LHLCCs, while some would consider it a once in a lifetime experience. Hence, the trans-Atlantic market has a consumer-base for both business models.

2.2. Revenue-related Insights

There are few mentions of revenue. For example, Tretheway (2004) studied the differences in operating characteristics of short-haul LCCs and hub-and-spoke FSNCs, and pointed out the strengths in low-cost carriers' revenue generation philosophy. Their strength lied in their priority system. First, a decision on capacity is made, then a pricing scheme is established that will allow them to generate the revenue required to cover cost of that capacity. Whereas FSNCs make a decision on capacity, then establish a pricing scheme to maximise revenue on a flight. In other words, LCCs maximise their profits while FSNCs maximise their revenue. The key distinction is LCCs' awareness of their costs and their need to cover it while FSNCs want to maximise revenue first then see if it will cover cost later, which obviously leads to a lack of optimisation and inefficiencies.

Work carried out by Tretheway in relation to revenue includes the intricacies of the double-counting of revenue from passengers. For example, a connecting passenger flies from A to C through B. The A-B segment counts the contributions of B-C and the B-C segment counts the contribution of A-B. This double counting amplifies the perceived revenue and gives the illusion that more capacity is needed to capitalise on this opportunity. This leads to economical inefficiencies and sets the stage for financial failure.

Morrell (2008) confirms Francis et al. (2007) by looking at revenue from commercial sources. He examines the effects and feasibility of lowering long-haul fares of both full-service and low-cost carriers below their normal to simulate competition between the two, only to realise that it is detrimental in the long run for both. Douglas (2010) brings mentions that if LHLCCs have premium classes, they can capture high-yield leisure traffic and price-sensitive corporate travellers.

Daft and Albers (2012) conducted a route profitability analysis and concludes that when analysing the viability of LHLC routes, revenue considerations are important. It provided insight on additional revenue generating techniques throughout the entire flight product broken down into pre-flight, check-in, in-flight, and post flight services. Upon reservation, additional revenue through seat reservations and exit seat booking can be achieved. Pre-flight services including Visa Services and airport pick-up are additional revenue sources. During check-in, excess baggage and late night check-in can be exploited. Priority waiting rooms and fast lanes can be charged for during passengers' stay at the airport. In-flight, meals, drink, entertainment, blankets and pillows are charged for, as well post-flight service such as airport pick-up. All these additional revenues can be categorised as ancillary revenues, since they are not included in the ticket purchased, which significantly contribute to profitability.

De Poret et al. (2015) conducts an assumption-based profitability analysis of LHLC routes, and found that larger wide-body aircraft offer economical operations on point-to-point routes with high leisure demand or with routes where sufficient feeder traffic can be found at both ends. Ancillaries are once again brought up, highlighting their importance for profitability. Wilken et al. (2016) estimates the potential traffic for long-haul point-to-point routes, and concludes that feeder traffic may be an important requirement for LHLCCs.

Soyk et al. (2018) shows great insight by analysing the trans-Atlantic market using their new REB metric, and after analysing a total of 33 airport-pairs found in 7 city-pairs in the year 2016, LHLCCs' REB is a mere 4% less than FSNCs. Soyk's 4 major findings are:

1. LHLCCs are negatively impacted by the lack of high-yield passengers resulting in lower yields overall. LHLCCs' cabin configurations are primed for low-yield passengers, with the large majority of the seats being economy seat and a few premium economy seats. This results in LHLCCs carrying 13% less premium passengers, which in turn results in LHLCCs generating 46% less yield per passenger per block hour than FSNCs. This is confirms Francis et al. (2007) and Douglas (2010) conclusions.
2. Soyk et al. (2017) shows that LHLCCs' point-to-point network has fewer connecting passenger and Soyk et al. (2018) expands on this finding and reveals the revenue diluting nature of connecting passengers. LHLCCs benefit from fewer connecting passengers, 14% less. 44% of passengers on FSNCs are connecting passenger and they contribute towards 27% of total revenue. Whereas 30% of passengers on LHLCC are connecting and contribute towards 25% of total revenue. FSNCs bear the cost of inconvenience for a passenger to fly an indirect route with one or multiple stops by offering the passenger a cheaper connecting fare while passengers on LHLCCs bear the cost themselves through self-connecting (Tretheway, 2004). This is confirms Tretheway (2004) conclusions.
3. LHLCCs are positively impacted by ancillary revenues. They generate 646% more ancillary revenue than FSNCs, and it constitute the majority of their profits (De Poret et al., 2015; Daft and Albers, 2012).
4. LHLCCs benefit from higher load factors. Across the North Atlantic, LHLCCs experienced an average load factor of 92.8%, while FSNCs experienced an average of 78.9%. LHLCC load factors beyond what De Poret et al. (2015); Daft and Albers (2012) assumed for LHLC flight.

3. Methodology

Route selection will be discussed; our application of Soyk et al. (2018)'s REB metric will be shown; and data sources will be listed.

3.1. REB

Despite a 10-25% decrease in costs compared to FSNCs (De Poret et al., 2015), a similar percentage increase in profit does not occur. This is due to numerous factors at play influencing the revenue side of profit. On a single route different carriers operate different *aircraft types*, with varying *cabin configurations*, and *seat densities* as per the specification outlined by the carrier (Clark, 2016). A simple seat-based revenue unit does not account for any of the variables aforementioned. A seat-based revenue unit requires aircraft to be of similar configuration, and routes of similar distance, to be indicative of the carrier's revenue performance.

RASK (Revenue per Available Seat-Kilometre) factors in seats and distance, but because of the non-linear relationship of RASK and distance flown (Doganis, 2019), and the generalisation of the seats regardless of their configuration, it still cannot be used to compare different aircraft type or routes. Soyk et al. (2018) developed a unit that overcame these shortcomings, called REB. It measures *revenue / equivalent flight capacity / block hour*. Revenue is the income generated from passenger-related activities such as ticket purchase and ancillary revenues. The definition of flight capacity in this study is the total area of the cabin space measured in m^2. *Equivalent* flight capacity is the equivalent number of economy seats forgone by the footprint of premium seats (i.e. the number of economy seats a 2 or 3-class aircraft could have had if the entire aircraft were to be filled with economy seats) according to the aircraft's exit limit[1] (Douglas, 2010). This begins to create a more interpretable unit where the common denominator is an equivalent seat capacity, which allows aircraft of different types and cabin configurations to be compared.

Flight time in block hours is used rather than distance. Although block hours do not accurately account for stage length, they do account for utilisation of aircraft. This includes total flight time at increased or reduced speeds, taxing in and out times. Therefore, block hours give insight on the utilisation of the aircraft used.

REB can now be used to benchmark airline against one another, with aircraft type, seat configuration and aircraft utilisation all factored in. The simplified equation for REB is shown below.

$$REB = \frac{Yield\ per\ passenger\ \times\ Load\ Factor \times\ Seat\ Density}{Block\ hours} \tag{1}$$

There are many sources of revenue for an airline as a result of its activity. However, it is narrowed down to the revenue generated from passengers. There are different types of passengers, the travellers considered here are direct [2] and connecting [3].

Revenue is calculated at an airport-pair level with all classes considered separately on a monthly basis. First (F), business (C), premium economy (PY), and economy (Y) class.

3.1.1. Direct passengers

Monthly direct revenue, $R^{MIDT}_{dir,t}$, is calculated using equation 2. The superscript '$MIDT$' denotes the database from which the value is sourced from. The data bases used will be explained in detail in subsection 3.3.

$$R^{MIDT}_{dir,t} = \sum_{i=\{F,C,PY,Y\}} F^{MIDT}_{dir,i,t} P^{MIDT}_{dir,i,t} \tag{2}$$

Where F^{MIDT}_{dir} is the direct fare in US$, and P^{MIDT}_{dir} is the number of passengers. Monthly direct revenue per cabin class is calculated then summed.

[1] Exit limit: maximum number of seat allowed for by the design of the aircraft

[2] In this study, a direct passenger's journey begins and starts between two airports with no stops in between. For example, consider the city pair Cairo International(CAI)-London Heathrow(LHR), a direct passenger travels from departure airport, CAI, to arrival airport, LHR, with no stops in the middle. This passenger is considered a *local* or *direct* passenger, i.e. their departure and arrival airport coincide with the airport pair in question.

[3] A connecting passenger is a passenger that travelled from Jomo Kenyatta International(NBO) to CAI, then from CAI to LHR. This is considered a *behind* passenger, i.e. the departure airport is different from the airport pair in question, but the CAI-LHR route is still flown. Iteratively, a passenger flying the route NBO-CAI-LHR is a 1-stop behind passenger.

3.1.2. Connecting passengers

Monthly connecting revenue, $R_{con,t}^{MIDT}$, is calculated using equation 3. The equation accounts for ALL behind routes, j, per airport pair. The stop before the airport-pair in question is the the feeder segment while the airport-pair route is the trunk segment.

$$R_{con,t}^{MIDT} = \sum_{i=\{F,C,PY,Y\}} \sum_{j=1}^{n} F_{con,t,i,j}^{MIDT} P_{con,t,i,j}^{MIDT} \frac{C_{trunk,j}}{C_{trunk,j} + C_{feeder,j}} \tag{3}$$

Where F_{con}^{MIDT} is the total fare charged for the whole 1-stop trip, and P_{con}^{MIDT} is the number of connecting passengers. $C_{WB,j}$ and $C_{NB,j}$ are the cost share of the trunk and feeder route respectively and are shown in equations 4 and 5.

These equations calculate the share of the fare, F_{con}, that the trunk and segment feeder obtain. They are from Swan and Adler (2006) and their study derived them using an engineering approach that involved categorising the constituents of aircraft cost to compute a generalised aircraft trip cost that is void of financial reporting errors. The resulting equations are a function of number of seat on the aircraft, S, and distance flown, D. The equations differentiate between aircraft type. Equation 4 is for wide-body (WB) aircraft (usually flown on trunk segments) whereas equation 5 is for narrow-body (NB) aircraft (usually flown on feeder segments). Soyk et al. (2018)'s assumption is that feeder aircraft on average tend to be narrow-body aircraft and they therefore generalises that rule on all feeder traffic. Whereas for this study, the equations are appropriately assigned by aircraft type.

$$C_{WB,j} = \frac{2(D_{trunk,j} + 2200)(S_{trunk,j} + 211)\text{”\$”}0.0115}{S_{trunk,j}} \tag{4}$$

$$C_{NB,j} = \frac{2(D_{feeder,j} + 277)(S_{feeder,j} + 104)\text{”\$”}0.019}{S_{feeder,j}} \tag{5}$$

3.1.3. Total Revenue

Adding revenue from direct and connecting passengers then dividing by total number of passengers gives the yield, as shown in equation 6, and is synonymous to gross yield, Y_{gross}, as described in equation 7.

$$Y_t^{MIDT} = \frac{R_{dir,t}^{MIDT} + R_{con,t}^{MIDT}}{P_{dir,t}^{MIDT} + P_{con,t}^{MIDT}} \tag{6}$$

$$Y_{gross,t} = Y_t^{MIDT} \tag{7}$$

The addition of average ancillaries earned per passenger and the subtraction of airport tax from the gross yield gives the net yield, as shown in equation 7.

$$Y_{net} = Y_{gross,t} - T_{pax}^{ITA} + A_{pax}^{var} \tag{8}$$

Now that net yield factors in different airport tax per airport-pair and ancillary revenue performance per airline, total revenue can be calculated by multiplying Y_{net}, monthly load factor, L, and total monthly seats scheduled to fly by the airline, S, as shown in equation 9

$$R_{total,t} = Y_{net,t} L_t^{MIDT} S_t^{OAG} \tag{9}$$

3.1.4. Revenue/Equivalent-seat/Block hour

Equation 10 describes how equivalent-setas (e-seats) are calculated. Different aircraft type can be flown on the same route. Even aircraft of the same type can have different seating configurations and densities. Therefore, an specific evaluation of each aircraft type on each airline is required. The e-seats flown per aircraft type, k, are obtained by multiplying the actual number of installed seats, S_k, with the ratio of e-seats to actually installed seats by aircraft type, e_k.

$$E_{total,t} = \sum_{k=1}^{m} S_{k,t}^{OAG} e_{k,t} \tag{10}$$

The average yearly revenue/e-seat (RE) per airport-pair is calculated using equation 11, where B is the block hours of a one-way flight between airport pairs.

$$RE = \frac{\sum_{t=1}^{12} R_{total,t}}{\sum_{t=1}^{12} E_{total,t}} \tag{11}$$

REB is then calculated using equation 12

$$REB = \frac{RE}{B} \tag{12}$$

3.2. Route selection

Soyk et al. (2018)'s selection criteria for routes is used. The city-pairs within the South-east Asian region are selected if they satisfy these criteria:

1. It is a long-haul flight as defined by Francis et al. (2007), where a minimum flight time of 6 hours categorises a flight as long-haul.
2. The airport pair has a minimum weekly flight frequency of 2, i.e. 104 return flights a year. Flights below the minimum would be considered chartered (Wilken et al., 2016).
3. Newly inaugurated routes need time for the public to become aware of them and thus generate stable revenue. Therefore, all city pairs must have two consecutive years of minimum yearly flights.
4. The airline must have a headquarter in either region, as airlines under the 5^{th} freedom carrying significant volumes of onward passengers whose fares are either excluded or wrongly allocated (Tretheway, 2004) disrupt the data set.

OAG was used to retrieve scheduled data on the whole of the South-East Asian market where AirAsia X and Scoot operate. When the criteria above is applied, the routes that filter through are shown in Table 1.

3.3. Data Sources

This subsection describes the data sources used and the rationale behind their choice. Data sources are summarised in Table 2.

Sabre's AirVision Market Intelligence Data Types (MIDT) [4] subscription database provides comprehensive data for all commercial functions for an airline to track performance, forecast future growth and provide data-driven insight for key commercial decisions. Passenger traffic, Schedules and Capacity data are all collected through a Global Distribution System (GDS) that considers only indirect bookings from online travel agents and global travel retailers. Unique to Sabre MIDT is its valuable sales data at different levels (i.e. Country level, Airport level etc) (Sabre, 2014). Sabre does not account for every fare purchase. Rather, it uses proprietary algorithms to produce O&D and Segment traffic numbers. These algorithms have been continuously enhanced for 30 years and are constantly cross-referenced against more than 40 external data sources to ensure the best results. Sabre MIDT is heavily relied by commercial and academic entities around

[4] https://emergo5.sabre.com/

Table 1: Routes selected for analysis (OAG, 2021)

#	City-Pair	Carrier Name	C.c	Airport-pair	Type	Flights 2018	Flights 2019
1	SIN-PER*	Singapore Airlines	SQ	SIN-PER	FSN	1460	1460
2		Qantas Airways	QF	SIN-PER	FSN	495	391
3		Scoot	TR	SIN-PER	LHLC	373	381
5	KUL-PER*	Malaysia Airlines	MH	KUL-PER	FSN	529	613
6		Malindo Airways	OD	KUL-PER	FSN	645	723
7		AirAsia X	D7	KUL-PER	LHLC	433	409
8	SIN-MEL	Singapore Airlines	SQ	SIN-MEL	FSN	1651	1694
9		Qantas Airways	QF	SIN-MEL	FSN	657	708
10		Scoot	TR	SIN-MEL	LHLC	295	395
11		Emirates	EK	SIN-MEL	FSN	365	365
12	SIN-SYD	Singapore Airlines	SQ	SIN-SYD	FSN	1800	1825
13		Qantas Airways	QF	SIN-SYD	FSN	724	750
14		Scoot	TR	SIN-SYD	LHLC	284	230
15		British Airways	BA	SIN-SYD	FSN	365	364
16	KUL-SYD	Malaysia Airlines	MH	KUL-SYD	FSN	702	730
17		AirAsia X	D7	KUL-SYD	LHLC	604	485
18	KUL-BJS	AirAsia X	D7	KUL-PEK	LHLC	448	365
19		Malaysia Airlines	MH	KUL-PEK	FSN	364	364
20		Air China	CA	KUL-PEK	FSN	206	151
21	SIN-OSA	Singapore Airlines	SQ	SIN-KIX	FSN	730	979
22		Scoot	TR	SIN-KIX	LHLC	209	189
23	KUL-OSA	Malaysia Airlines	MH	KUL-KIX	FSN	359	402
24		AirAsia X	D7	KUL-KIX	LHLC	505	366
25	KUL-TYO	Malaysia Airlines	MH	KUL-NRT	FSN	589	623
26		All Nippon Airways	NH	KUL-HND	FSN	365	365
27		AirAsia X	D7	KUL-HND	LHLC	-	-
28		All Nippon Airways	NH	KUL-NRT	FSN	365	365
29		Japan Airlines	JL	KUL-NRT	FSN	365	365
30		AirAsia X	D7	KUL-NRT	LHLC	365	365
31	KUL-JED	Saudi Arabian Airlines	SV	KUL-JED	FSN	709	807
32		Malaysia Airlines	MH	KUL-JED	FSN	256	169
33		AirAsia X	D7	KUL-JED	LHLC	158	199
34	SIN-JED	Saudi Arabian Airlines	SV	SIN-JED	FSN	172	172
35		Scoot	TR	SIN-JED	LHLC	134	147

the world (Sabre, 2014). Official Airline Guide (OAG)[5] is a subscription database that accounts for 96% of global passenger itineraries and contains vast information (57 million flight status records updated yearly) on the schedules set by more than 980 airlines and 4000 airports. ITA Matrix Airfare Search provides a detailed breakdown of fare and tax cost between two airports

Finding ancillary revenue per passenger performance of airlines is difficult. Information is scarce and financial reports do not publish the necessary detail to derive it. However, a report by Ideal Works was found to have information about the top airlines generating ancillary revenue per passenger in 2018 (Sorensen, 2016), as shown in Table **??**. The table contains information on two airlines available in our data set, Qantas Airways and AirAsia X. Ideal Works estimates that the average ancillary revenue per passenger is $24. From

[5]http://analytics.oag.com

Table 2: Variables and their data sources.

Variable	Source
F_{dir}	MIDT - Leg/Flow
P_{dir}	MIDT - Leg/Flow
F_{con}	MIDT - Leg/Flow
P_{con}	MIDT - Leg/Flow
D_{trunk}	OAG - Schedule
S_{trunk}	OAG - Schedule
D_{feeder}	OAG - Schedule
S_{trunk}	OAG - Schedule
T_{pax}	ITA Matrix
A_{pax}	Various
L	MIDT - Leg/Statistics
S	OAG - Schedule
S_k	OAG - Schedule
$exitlimit$	Various
S_{ki}	Various
B	OAG - Schedule

this, estimations were made on the the remaining airlines[6].

Aircraft exit limits needed to calculate equivalent seat ratios were found by logging all aircraft used on all routes and finding their each aircraft code's exit limit based on their type certificate found on manufacturer websites, airport planning documentations and journal papers (Airbus, 2002; Boeing, 2015, 2018, 1998; Soyk et al., 2018).

All the data was extracted in CSV format and a python script was written to import and clean the data, execute all aforementioned equations and plot the graphs. The os, pandas, numpy and matplotlib libraries were used and facilitated the management of such a complex data set with ease.

4. Results and Discussion

Results show that there is a 26.6% difference in REB between FSNCs and LHLCCs, as shown in Figure 1. The FSNCs overall perform better than LHLCCs, more so in the South-East Asian market than in the North Atlantic market where a difference of 4% was found Soyk et al. (2018). The results are not as shockingly close as those found on the North Atlantic market. The North Atlantic market is well established and lucrative, especially for routes originating in London going to the East or West Coast of the United States. New York and Los Angeles are characterised with being large economies and are home to numerous of the Fortune 500 companies.

Figure 2 shows the REB of all airlines grouped in their respective city-pairs with the city-pair REB means dotted horizontally for perspective on LHLCCs relative performance to the overall city-pair performance. Also, yield per passenger is plotted on the right y-axis to contrast yield performance with REB. There are a number of key findings. First, out of the eleven city-pairs, four of them have LHLCCs that operate at a greater than average level. A similar trend is found in the Southeast Asian market where large economy city-pairs find themselves to have the highest yielding passengers, namely routes originating in Singapore and Kuala Lumpur going to Osaka, Tokyo and Sydney. It is found that LHLC carriers perform at an above average REB level in KUL-TYO, SIN-MEL and SIN-JED. LHLC perform at near average REB levels in KUL-OSA, while the rest perform below average. Soyk's observation that LHLC carriers perform better at shorter distances (i.e. 5500-6200 km) can be somewhat seen in the Southeast Asian market. KUL-TYO and SIN-MEL have distances of 5400 km and 6080 km respectively and their LHLCCs are outperforming their FSN counterpart. SIN-JED is the exception; being the farthest city-pair at 7379 km. However, there is large

[6]Ancillary per passenger: Spirit \$50.94, Allegiant \$50.01, Frontier \$47.62, Jet2.com \$43.91, Qantas Airways \$41.15, United \$36.64, American \$35.56, Virgin Australia \$34.74, AirAsia X \$34.28, Hawaiian \$32.70.

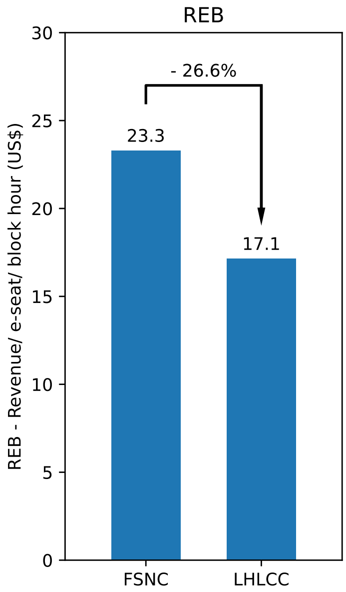

Figure 1: Mean difference in REB for Southeast Asian

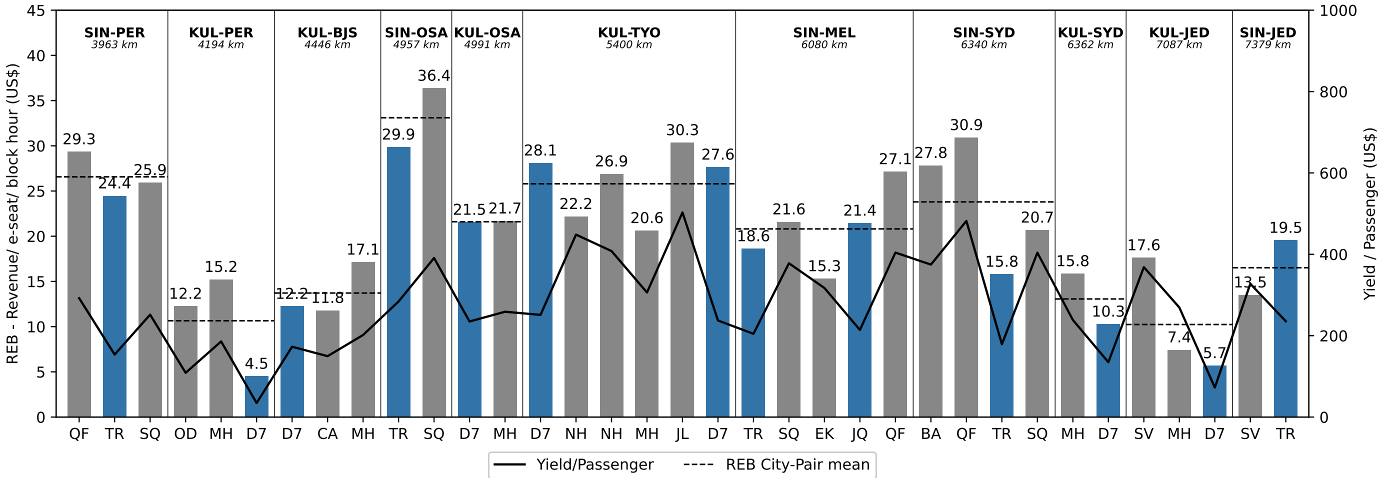

Figure 2: REB values for airlines on different routes

demand on a route going to Jeddah for Islamic trips such as Omrah or Hajj (the Pilgrimage), religious acts that are considered obligatory to those who can afford it, hence creating sufficient demand to drive revenue.

The right-hand side axis of Figure 2 shows the Yield/Passenger and it can be observed how LHLCCs score lowest in each city-pair. However, REB shows us that the difference between the carriers is not as drastic as yield, for example, in KUL-TYO D7 (AirAsiaX) has the lowest yield/passenger but has the second and third highest REBs. In SIN-JED, S7 (Saudi Airline) has a higher Yield/Passenger but the picture is reversed when viewing REB. This is to be expected and is the reason behind a REB analysis.

Characterising revenue goes beyond summing up what the passengers pay the airline. Other factors are involved and are shown in figure. Figure 3 shows revenue and operating characteristics influencing REB.

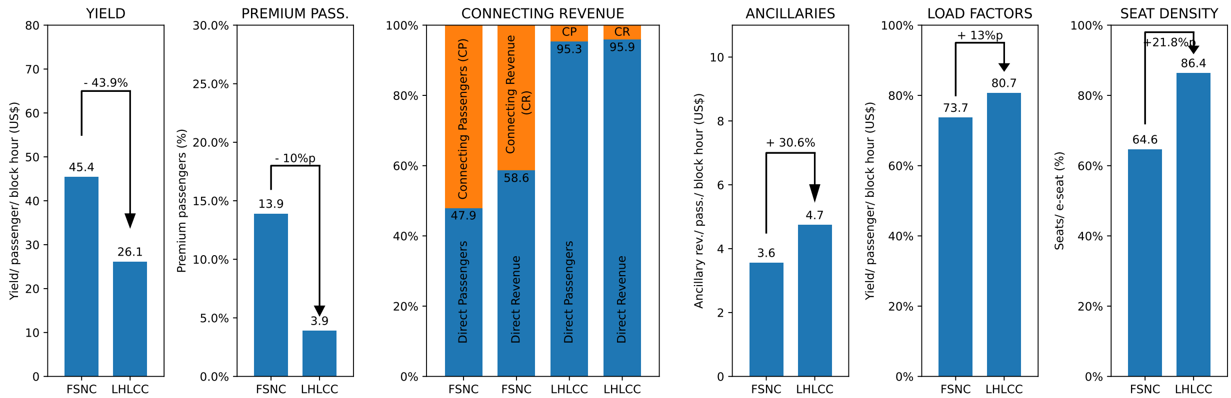

Figure 3: Differences in revenue and operating characteristics influencing REB aggregated by carrier type, weighted by number of passengers

When observing mean yield per passenger per block hour, LHLCCs generating around a half of what FSNCs manage to generate. This does not come by surprise since LHLCCs competitive edge is their low fares. On all city pairs LHLCCs earn the lowest yield per passenger.

LHLCCs have 10%p (percentage points) fewer premium passengers onboard than FSNCs. LHLC carriers aim for higher seat densities which does not allow them to have spacious premium seats. This is evident by LHLCCs having higher seat densities at around 86.4% of their exit-limit; while FSNCs are at 64.6% their exit-limit. Load factors on LHLCCs are also higher than FSNCs at 80.7%. This shows how LHLCCs attempt to maximise aircraft utilisation to capitalise on the efficiencies gained.

The revenue diluting effect of connecting passengers can also be seen in the South-East Asian market. LHLCCs carry significantly fewer connecting passengers and experience minimal revenue dilution when compared to FSNCs. LHLCCs in the Southeast Asian market also does not have as many connecting passengers accounted for in Sabre MIDT when compared to the connecting passenger numbers in the North Atlantic market. This could be from self-connecting passengers who buy separate tickets for different parts of the journey and bear the responsibility of transferring their own luggage and repeated check-in. For FSNCs, 47.9% of their total passengers are direct and they contribute towards 58.6% of their total revenues, while for LHLCCs, 95.3% of their total passengers are direct and they contribute towards 95.9% of their total revenue.

Ancillaries per block hour shows LHLCCs advantage over FSNCs. In Soyk et al. (2018), the difference in ancillaries was 646%p rather than 6.3%p. This is because of a difference in assumptions and estimations. Soyk et al. (2018) assumes $10 for every economy passenger flying full-service and $59 for every passenger, irrespective of class and airline, for LHLC passengers. Our assumption ins this study are based on average ancillary revenues per passengers found in financial statements and reports, as shown in Table **??**. Also, this result shows that FSNCs have realised the benefits of ancillary revenues and are implementing it into their model.

Table 3 shows key variables extracted from the REB calculation process with each city-pair greyed and the LHLCCs in bold. The table reveals numerous observations. With regards to passengers, FSNCs competitors achieve the highest in every airport-pair with the exception of KUL-HND, KUL-JED and SIN-JED. Haneda Airport offers greater capacity to airline than Narita International airport, which is know for its saturated, limited and highly competitive capacity. Although further from Tokyo city centre, Haneda airport's convenient public transportation allows it to be an attractive destination to price-sensitive passengers and high-yield passengers. AirAsiaX can be seen to capitalise on this opportunity provided by Haneda airport and is generating above average revenue and REB. Once again, high passenger numbers are benefited from the JED destination because of religious travel.

It can also be seen how FSNCs outperform LHLCCs with regards to total revenues. On the KUL-TYO, KUL-SYD and KUL-JED city-pairs, LHLCCs are performing competitively against their FSNC counterpart, whereas on the remaining city-pairs LHLCCs are generating a fraction of what their competitors making.

Equivalent seats show how each each airline model and airline utilise their cabin space, with LHLCCs at a equivalent seat ratios (e) between 86-89% while FSNCs range between 48-87%. The use of spacious premium, business and first class seats on FSNCs contributes to the lower e ratios, while LHLCCs seat configurations where the aim is to densely pack as many seats as is comfortable to the passenger is the reason why they are so high.

Table 3: Key variable in REB analysis.

Origin Airport	Destination Airport	Airline	Passengers	Seats	Net Yield	R	E	e	RE	B	REB	Y/P/B
SIN	PER	QF	67,418	103,343	292.2	23,498,833	153,342	0.67	153.2	5.2	29.3	55.9
SIN	**PER**	**TR**	**126,744**	**120,989**	**153.7**	**17,131,482**	**135,681**	**0.89**	**126.3**	**5.2**	**24.4**	**29.8**
SIN	PER	SQ	303,369	444,351	251.7	85,398,934	633,260	0.70	134.9	5.2	25.9	48.4
KUL	PER	OD	90,093	123,858	108.7	10,436,345	148,241	0.84	70.4	5.8	12.2	18.9
KUL	PER	MH	72,809	133,197	185.9	15,329,109	177,708	0.75	86.3	5.7	15.2	32.8
KUL	**PER**	**D7**	**129,231**	**154,193**	**34.5**	**4,455,092**	**179,960**	**0.86**	**24.8**	**5.5**	**4.5**	**6.3**
KUL	**PEK**	**D7**	**73,100**	**137,605**	**172.8**	**12,686,877**	**160,600**	**0.86**	**79**	**6.5**	**12.2**	**26.8**
KUL	PEK	CA	13,055	36,724	149.6	3,778,466	49,960	0.74	75.6	6.4	11.8	23.3
KUL	PEK	MH	82,729	105,270	201.7	17,324,189	159,720	0.66	108.5	6.3	17.1	31.8
SIN	**KIX**	**TR**	**49,973**	**64,545**	**284.1**	**14,101,911**	**73,530**	**0.88**	**191.8**	**6.4**	**29.9**	**44.2**
SIN	KIX	SQ	264,294	323,957	391	108,305,345	459,141	0.71	235.9	6.5	36.4	60.3
KUL	**KIX**	**D7**	**96,259**	**137,982**	**234.9**	**22,846,080**	**161,040**	**0.86**	**141.9**	**6.6**	**21.5**	**35.6**
KUL	KIX	MH	88,418	115,336	258.9	24,098,261	176,880	0.65	136.2	6.3	21.7	41.2
KUL	**HND**	**D7**	**124,975**	**137,605**	**251.1**	**31,969,785**	**160,600**	**0.86**	**199.1**	**7.1**	**28.1**	**35.4**
KUL	HND	NH	47,325	86,969	448.4	23,550,418	153,300	0.57	153.6	6.9	22.2	64.7
KUL	NRT	NH	34,859	85,997	408	27,646,557	149,634	0.57	184.8	6.9	26.9	59.4
KUL	NRT	MH	147,502	209,290	306.2	48,722,821	338,135	0.62	144.1	7	20.6	43.8
KUL	NRT	JL	52,530	74,095	502.9	32,665,823	153,300	0.48	213.1	7	30.3	71.6
KUL	**NRT**	**D7**	**8,341**	**9,048**	**237.3**	**2,018,364**	**10,560**	**0.86**	**191.1**	**6.9**	**27.6**	**34.3**
SIN	**MEL**	**TR**	**108,062**	**142,143**	**204.6**	**22,689,065**	**160,284**	**0.89**	**141.6**	**7.6**	**18.6**	**26.9**
SIN	MEL	SQ	320,139	481,148	378	149,555,732	934,591	0.51	160	7.4	21.6	51
SIN	MEL	EK	40,838	131,498	317.1	22,800,273	204,992	0.64	111.2	7.3	15.3	43.6
SIN	**MEL**	**JQ**	**26,383**	**31,825**	**214.2**	**6,131,662**	**39,003**	**0.82**	**157.2**	**7.3**	**21.4**	**29.2**
SIN	MEL	QF	145,830	268,802	404.2	90,849,206	453,692	0.59	200.2	7.4	27.1	54.8
SIN	SYD	BA	51,285	108,108	374.7	34,530,740	160,160	0.68	215.6	7.8	27.8	48.4
SIN	SYD	QF	160,789	281,647	482	114,165,313	470,592	0.60	242.6	7.9	30.9	61.4
SIN	**SYD**	**TR**	**80,317**	**82,432**	**179**	**11,475,165**	**93,129**	**0.89**	**123.2**	**7.8**	**15.8**	**22.9**
SIN	SYD	SQ	395,690	611,616	404	196,718,710	1,224,940	0.50	160.6	7.8	20.7	52
KUL	SYD	MH	166,183	211,708	238.6	42,607,341	322,439	0.66	132.1	8.3	15.8	28.6
KUL	**SYD**	**D7**	**130,527**	**182,845**	**134.8**	**18,295,139**	**213,400**	**0.86**	**85.7**	**8.3**	**10.3**	**16.2**
KUL	JED	SV	68,349	261,902	368.5	54,186,850	356,610	0.73	151.9	8.6	17.6	42.7
KUL	JED	MH	35,930	67,288	269.3	7,358,265	104,751	0.64	70.2	9.5	7.4	28.5
KUL	**JED**	**D7**	**70,957**	**75,023**	**72.6**	**4,816,659**	**87,560**	**0.86**	**55**	**9.7**	**5.7**	**7.5**
SIN	JED	SV	21,559	51,256	327.6	8,721,588	72,240	0.71	120.7	8.9	13.5	36.6
SIN	**JED**	**TR**	**44,111**	**49,639**	**235.4**	**10,623,010**	**56,748**	**0.87**	**187.2**	**9.6**	**19.5**	**24.6**

5. Conclusion

Soyk et al. (2018)'s hypothesis holds true in the South-East Asian LHLC market. However, his clain on the North Atlantic market, "Despite lower average fares of LHLCCs compared to FSNCs, revenue per equivalent flight capacity unit is comparable" differs in the South-East Asian market. On average the Atlantic has a difference of 4% while the Southeast Asian is 26.6%. The key point is, despite drastically lower yields, LHLCCs, from an REB point of view, are competitive. This study also quantitatively answers the four research questions and confirms the findings on the North Atlantic market (Soyk et al., 2018)

1. LHLCCs yield suffer because of lower economy-class fares and a lack of high yield passengers. They generate 43.9% less yield than FSNCs with 10% less premium passengers, and in the North Atlantic market they generate 46% less yield with 13% less premium passengers.
2. LHLCCs revenues are positively impacted by the lack of revenue-diluting connecting passengers. For FSNCs, 47.9% of their total passengers are direct and they contribute towards 58.6% of their total revenues, while for LHLCCs, 95.3% of their total passengers are direct and they contribute towards 95.9% of their total revenue.

3. LHLCCs are positively impacted by ancillary revenues. They generate 30.6% more than FSNCs, while on the North Atlantic market they generate 646% more
4. LHLCCs operate with higher average load factors and higher average seat densities due to the absence of large premium, business or first class seats. LHLCCs enjoy 13%p more load factors with an added 21.8%p in there seat densities than their competition. For the North Atlantic market, the same can be seen with LHLCCs operating at 14%p more load factors and 19% more seat density.

The Southeast Asian market is not as mature as the North Atlantic market (Global, 2002). In terms of deregulation, it still has more to accomplish, with the EU-ASEAN open skies agreement nearing completion (Casey, 2020). The larger difference in REB between FSNCs and LHLCCs in the Southeast Asian market can be attributed to a lack of demand because of the constrained freedoms of the air. Seems to be that LHLCCs indeed do require a mature market for them to operate successfully or at least at a competitive level.

All in all, there is much to learn about the LHLC model and the environment it needs to thrive in. Discovering a new metric like the REB shines great light and deep insight on the inner workings of the LHLC model. It is hoped that more research goes into this curious model. It connects the world further and offers cost-effective solutions for people on a budget.

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