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A data-driven approach for characterising revenues of South-Asian long-haul low-cost carriers per equivalent flight capacity per block hour

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ABSTRACT

This study sets out to investigate the revenue characteristics of long-haul low-cost carriers (LHLCCs) in the Southeast Asian market using a recently established metric that calculates *revenue per equivalent flight capacity per block hour* (REB). REB allows for the accurate comparison of airlines on different routes with varying cabin configurations, and stage lengths. The majority of the data was sourced from Sabre MIDT and OAG, while supplementary data were from other various sources. In addition to REB, the study investigates: How do LHLCCs yields compare to full-service network carriers (FSNCs)? Are LHLCCs positively impacted by smaller share of connecting passengers? Are LHLCCs positively impacted by ancillary revenues? Do LHLCCs benefit from higher load factors and seat densities?

Results show that LHLCCs 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. On a route-level, some LHLCC operations can equally perform or outperform competition's revenue performance. Furthermore, the findings are mostly consistent with earlier REB research conducted on the North Atlantic market by Soyk et al. (2018). Revenue and operating characteristic showed the same trends in both markets, although to varying degrees.

This study exposes, with high detail, the revenue generating inner-workings of the elusive long-haul low-cost model in its second largest market, and compares it on equal grounds to their full-service network competition. We learn that airlines can drive the airfare down while minimising the loss of revenue per flight capacity of the aircraft by adjusting for the numerous variables that directly impact it, such as seat density, cabin configuration, ancillary revenues, load factors, and percentage of connecting passengers.

1. Introduction

In many industries, competitors opt to take one of three strategies to achieve success against one another that include; cost leadership, differentiation or focus differentiation (Porter, 1985). In the airline industry, the two most notable competing strategies are the cost leadership and differentiation strategies represented by 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 to medium-haul markets when competing with the FSNCs in most global markets — notable examples include Southwest airlines, Ryanair, AirAsia, Jetstar, Azul and Indigo. These carriers operate on a very different operating platform than that of the FSNCs as they enshrine the concept of 'low cost' into their organisational culture and offer low fares in exchange for eliminating many of the traditional passenger services. Their routes also operate on a point-to-point network structure, eliminating the inefficiencies experienced by the hub-spoke network structure. Consequently, these carriers have caused a paradigm shift in the traditional short-medium haul marketplace and have precipitously gained market share and overall have been the most successful airline business model of all time. Airline management then extended this into the long haul markets, but this endeavour has been fraught with difficulties. Many attempts of operating long-haul low-cost carriers (LHLCCs) have failed, while a handful are still operating the model but with uncertainty. The model does not guarantee success or profits, and therefore is yet to be proven.

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The literature concerned with the long-haul low-cost model is small in quantity and unbalanced in research topics. With regards to the financial performance of LHLCCs, studies investigated the cost reductions of the model and compared them to FSNCs where the data was retrieved from reliable sources (Francis et al., 2007; Morrell, 2008; Wensveen and Leick, 2009; Douglas, 2010; Moreira et al., 2011; Whyte and Lohmann, 2015), while studies with insight on revenue generation usually use their own empirical assumptions that vary from study to study (Tretheway, 2004; Francis et al., 2007; Morrell, 2008; Douglas, 2010; Daft and Albers, 2012; De Poret et al., 2015; Wilken et al., 2016). However, this changed when Soyk et al. (2018) developed a metric that calculated the *revenue/equivalent flight capacity/block hour* (REB) for the North Atlantic market. They applied a commercial input that formulated a more robust narrative that in turn created a new branch in the literature to do with data-driven revenue analytics that was tested on the long-haul low-cost model.

This paper aims to add to this branch and fill the revenue gap in the long-haul low-cost literature by characterising the revenue characteristics of the Southeast Asian 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. 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 unique about the Southeast Asian market is that it is home to two of the largest LHLCCs, AirAsia X and Scoot, with 13% and 7% respectively of the global long-haul low-cost market in terms of seat capacity for 2019 (OAG, 2021). In addition, their headquarters are just 300 km away from each other, offering the opportunity to analyse two LHLCCs who are geographically very close to each other and who offer flights to similar destinations. This allows for the dataset to be large and extensive, allowing for a reasonable comparison of FSNCs and LHLCCs.

The results will complement (Soyk et al., 2018)'s findings conducted on the North Atlantic market and help create a more cohesive analytical picture of the long-haul low-cost model.

The paper is structured as follows: Section 2 presents a review of previous revenue studies on the long-haul low-cost model. Section 3 consists of the methodology where all logical and technical steps are explained in detail. The results and discussion are presented in Section 4. Finally, Section 5 concludes the paper.

2. Literature review

This literature review will focus first on data-driven studies on the long-haul low-cost model in general, and then on revenue-related insights exclusively. Data sources used in these studies and the geographical regions where the studies were conducted will be discussed to create an understanding of what, how and when the long-haul low-cost model has been studied.

2.1. LHLCCs data-driven studies

Francis et al. (2007) examines the 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 flights. By examining compiled statistics by aviation authorities such as IATA, CAA, and AEA, the study concludes that FSNCs are dependent on high yield First and Business class passengers, that often use this high premium revenue generated to cross-subsidise the economy seats by being able to offer more attractive lower price tickets. This in turn severely challenges the LHLCC business model. In addition, the study compared the cost advantages of traditional low-cost carriers that operate in the short-haul markets and found that LHLCC operations can be possible only in large markets where demand is high like London to Chicago.

With data sourced from Boeing, CAA, and academically published data, Morrell (2008) observes the cost advantages of an intra-European low-cost carrier and compares the cost advantages between short-haul and long-haul flights 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 a low competitive response from the incumbent airlines. Such factors contributed to doubts over the viability of the business model by the author.

From 2010 to 2021, in-depth quantitative studies started to dig deeper into the long-haul low-cost model. Moreira et al. (2011) built a cost simulation for a LHLCC based on the Boeing 767–300 and demonstrated that the cost advantages did not exceed 10% when compared to FSNCs on the long haul markets. The study also found that LCCs enjoyed 50% cost savings on the short to medium-haul market. Daft and Albers (2012) conducted a route *profitability* analysis on long-haul low-cost flight scenarios and found that such flights are possible if suitable trunk routes are identified and the service is unbundled, i.e. instead of an all-inclusive ticket, the airfare is broken up and the passengers are prompted to pay for whichever service/product they require. For example, seat allocation, baggage, in-flight catering, blankets, in-flight entertainment, etc. The analysis used common industry, manufacturer, and operator data to construct the cost structure. They verified their assumption with experienced airline managers to ensure realistic parameters for their study.

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. The bulk of their data was sourced from Boeing and applied to two routes, namely London Gatwick–Los Angeles International and Manchester–Newark Liberty International. They discovered that fluctuations in demand are more detrimental to profitability than fluctuations in fuel price. When load factors were reduced to 60% (from the average 80%–85%), and extra cargo revenue is accounted for (due to freed up space from fewer passengers checking in bags), a lower load factor was found to be more damaging than increasing fuel prices.

In the history of aviation, long-haul flights were almost always full-service, with the exception of Charter Airlines together with a handful of earlier LHLCC innovators such as Laker Airways in 1977 and Peoples Express in 1983, followed some 30 years later by Hong Kong's Oasis Airline and the Canadian Zoom Airline, which all subsequently failed. The long-haul low-cost model aims to fly its passengers for 6–12 h with comfort and amenities stripped away. The question of a passenger's willingness to purchase additional amenities naturally arises. Jiang (2013) surveyed long-haul passengers in the South-East Asian/Pacific market, which revealed a different set of scenarios. Long-haul low-cost passengers prioritised assurance first (i.e. feeling safe when flying with an airline) followed by satisfaction with the airfare when flying with LHLCCs like Jetstar and AirAsia X. Meanwhile, passengers travelling with the full-service network airlines prioritised satisfaction with the service, followed by flight schedule. The study also found that expectations, which differ from one socio-cultural demographic to the other, play a large role in a passenger's sense of satisfaction with the airfare.

Hunt and Truong (2019) surveyed 1412 passengers flying within the trans-Atlantic market on the factors that impacted their choice of

LHLCCs and FSNCs. When *choosing between* LHLCCs, the airfare became the primary reason for selection, followed by comfort. When *choosing between* FSNCs, service became elevated to being the main reason for choice, closely followed by the on-time flight scheduling. When *loyalty* was investigated, passengers are more loyal to a FSNC that offers an all-inclusive service as higher tiers were attached with additional privileges that added significant value, compared to a LHLCC that is void of such a privilege. When asked about *remaining or switching* from a FSNC or a LHLCC, a spectrum of answers emerged. Some FSNC passengers would only want to travel with a full-service, while others would welcome the switch to a LHLCC primarily because of its cheaper air fare. Meanwhile, some LHLCC passengers would enthusiastically continue flying with LHLCCs, while others would consider it once in a lifetime experience. The trans-Atlantic market has a diverse consumer base that appeals to both airline business models. This confirms the claims by Douglas (2010) who argued that if LHLCCs have premium classes, they can capture both high-yield leisure traffic and price-sensitive corporate travellers.

Through a data exploratory approach of the OAG database, Zuidberg and de Wit (2020) explores the network characteristics of LHLCCs in the North Atlantic market. The study shows growth of the long-haul low-cost model, primarily induced by Norwegian airlines. Nonetheless, the model's network follows characteristics defined in earlier literature such as the high use of secondary airports, feed traffic that increased the overall passenger throughput and the efficient use of newer aircraft technologies.

Annual reports and OAG showed how LHLCCs had an evident effect on the routes they operated in, as they positively impacted the competitive landscape by decreasing the HHI of FSNCs by around an order of magnitude more than if LHLCCs were not involved (0.17 from 2015 to 2019 as opposed to 0.02) (Zuidberg and de Wit, 2020). Soyk et al. (2021) interrogates the effects of LHLCCs on competition even further by specifically analysing the effect the model has on North Atlantic fares. Through the use of International Air Transport Association's "Market Intelligence Services" (MarketIS), and schedule database Diio LLC, Long-haul low-cost activity results in an 11%–18% decrease in economy class fares and a 2%–6% reduction in business class fares.

2.2. Revenue-related insights

There are few mentions of revenue in the literature pertaining to LHLCCs. To set the stage, Tretheway (2004) studied the differences in operating characteristics of point-to-point low-cost carriers and hub-and-spoke FSNCs by analysing their annual reports and respective data from IATA. Results showed strengths in the low-cost carriers' revenue generation philosophy. Albeit the study was done on low-cost carriers in the short to medium-haul, the study emphasises a revenue characteristic of an airline that adopts a cost leadership strategy that can be implemented at any stage length. Their strength resided in their bespoke decision on capacity management whereby a pricing mechanism is established that will allow them to generate the sufficient revenue to cover cost of transporting that seat capacity. Whereas FSNCs make a different decision in relation to capacity as they establish a pricing scheme to maximise revenue on a flight. In other words, low-cost carriers maximise their profits, while FSNCs maximise their revenue. The key distinction is that low-cost carriers' are fully aware of their costs and must find their breakeven load factor and pricing scheme, while FSNCs aim to maximise revenue first, then cover cost second. An important consideration for FSNCs is they need to factor in their overall network as their short-haul traffic feeds their long haul network, which can ultimately lead to a lack of optimisation and can induce inefficiencies.

Research carried out by Tretheway included the intricacies of the double-counting of passenger revenues. For example, a connecting passenger flies from city A to city C through a hub 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 economic inefficiencies and sets the stage for financial dilution.

Morrell (2008) confirms Francis et al. (2007) by looking at revenue from commercial sources. The author examines the effects and feasibility of lowering long-haul fares of both full-service and low-cost carriers below their nominal value normal to simulate competition between the two, only to realise that it is detrimental in the long run for both.

Daft and Albers (2012) conducted a route profitability analysis and concluded that when analysing the viability of long-haul low-cost routes, revenue considerations are important. The study provided insights on the additional revenue-generating opportunities throughout the entire flight broken down into reservation, pre-flight, check-in, in-flight, and post flight services. With respect to reservation, additional revenue can be garnered by charging for seat allocation (window or aisle) as well as more lucrative revenue streams such as booking an exit row seat that has a much more generous seat pitch than the other seating configuration. Pre-flight services included visa services and airport pick-up were viewed as incremental revenue sources. During check-in, excess baggage and late-night check-in can be extrapolated. Lounges and fast track security lanes can be offered to passengers while at the airport. While in-flight, meals, drinks, entertainment, blankets and pillows are distributed and payment is taken, while post-flight, ground transportation services such as pick-up from the airport can also be aggregated to the revenue intake. All these additional revenues can be categorised as ancillary revenues, since they are not included in the original price of the ticket, which significantly contributes to the overall profitability.

De Poret et al. (2015) conducts an assumption-based profitability analysis of long-haul low-cost 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 focused upon, highlighting their importance in generating profitability. Wilken et al. (2016) estimated the potential traffic for long-haul point-to-point routes and concluded that feeder traffic is an important requirement for LHLCCs.

Soyk et al. (2018) conducted an in-depth analysis of the trans-Atlantic market through their revenue per equivalent seat capacity per block hour (REB) metric which examined 33 airport-pairs from 7 key city-pairs in 2016. The study involved one of the most comprehensive collections of data. Flight schedule data, MIDT data, Skyscanner, and U.S Department of Transport reports were all combined. It found that the LHLCCs' REB is a mere 4% less than FSNCs. Overall, Soyk's 4 major findings were:

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 seats with only 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; 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 actually benefits from 14% fewer connecting passengers. The study found that 44% of passengers on FSNCs were connecting passengers and they contributed 27% to the total revenue. Whereas 30% of passengers on LHLCC were connecting and contributed towards 25% of total revenue. FSNCs bear the cost of inconvenience for a passenger to fly an indirect route as they must take one, two or multiple stops and consequently offer passengers a cheaper fare for the inconvenience of connecting, while passengers on LHLCCs bear the cost themselves through self-connecting (Tretheway, 2004). This also 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 long-haul low-cost flight.

3. Methodology

Our application of Soyk et al. (2018)'s REB metric will be shown, the data sources will be listed, and the route selection analogy will also be discussed.

3.1. REB

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, 2017). A simple seat-based revenue unit does not account for any of the variables aforementioned. To be indicative of the carrier's revenue performance a seat-based revenue unit requires routes of similar distance, and aircraft to be of similar configuration (1-class, 2-class or 3-class configurations, containing a mixture of economy, premium economy, business and first class seats).

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 per equivalent flight capacity per block hour. Equivalent flight capacity is the equivalent number of economy seats forgone by the footprint (surface area) of premium seats (i.e. if the entire aircraft was configured with economy class seats only) 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 reflect for stage length, but they do account for aircraft utilisation. This includes total flight time at increased or reduced speeds as well as taxi in and out times. Therefore, block hours give valuable insights to the level of aircraft utilisation.

REB can now be used to benchmark one airline against another, when aircraft types, seat configurations 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. The passengers considered here are direct[2] and connecting.[3]

[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.

Revenue is calculated at an airport-pair level with all classes considered separately on a monthly basis. The cabin classes for this study are identified as follows: First (F), business (C), premium economy (PY), and economy (Y) class.

Soyk et al. (2018)'s equations will be described below alongside alterations made to them in this study.

3.1.1. Direct passengers

Monthly direct revenue, $R^{MIDT}_{dir,t}$, is calculated using Eq. (2). The superscript '*MIDT*' denotes the Sabre MIDT database from which the data is sourced from. The data bases used will be explained in detail in Section 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.

3.1.2. Connecting passengers

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

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

where F^{MIDT}_{con} is the total fare charged for the entire 1-stop trip, and P^{MIDT}_{con} is the number of connecting passengers. $C_{trunk,j}$ and $C_{feeder,j}$ are the cost share of the trunk and feeder segments and are shown in Eqs. (4) and (5) respectively. 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 seats on the aircraft, S, and distance flown, D. The equations differentiate between aircraft type. Eq. (4) is for wide-body (WB) aircraft whereas Eq. (5) is for narrow-body (NB) aircraft. Soyk et al. (2018)'s assumption is that feeder aircraft on average are narrow-body aircraft and they therefore generalise all feeder aircraft to be narrow-body, however for this study, the equations are appropriately assigned by aircraft type. If the feeder (or trunk) aircraft is wide-body, then $C_{WB,j}$ substitutes $C_{feeder,j}$ (or $C_{trunk,j}$). If the feeder (or trunk) aircraft is narrow-body, then $C_{NB,j}$ substitutes $C_{feeder,j}$ (or $C_{trunk,j}$).

$$C_{WB,j} = \frac{2 \times (D^{OAG}_{WB,j} + 2200) \times (S^{OAG}_{WB,j} + 211) \times \text{“\$”}0.0115}{S^{OAG}_{WB,j}} \tag{4}$$

$$C_{NB,j} = \frac{2 \times (D^{OAG}_{NB,j} + 277) \times (S^{OAG}_{NB,j} + 104) \times \text{“\$”}0.019}{S^{OAG}_{NB,j}} \tag{5}$$

3.1.3. Total revenue

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

$$Y^{MIDT}_{t} = \frac{R^{MIDT}_{dir,t} + R^{MIDT}_{con,t}}{P^{MIDT}_{dir,t} + P^{MIDT}_{con,t}} \tag{6}$$

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

The addition of average ancillaries earned per passenger per airline and the subtraction of airport tax per airport-pair from the gross yield gives the net yield, as shown in Eq. (7).

$$Y_{net} = Y_{gross,t} - T^{ITA}_{pax} + A^{var}_{pax} \tag{8}$$

Total revenue can now be calculated by multiplying Y_{net}, monthly load factor, L, and total monthly seats scheduled to fly by the airline, S, as shown in Eq. (9).

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

3.1.4. Revenue/equivalent-seat/block hour

Eq. (10) describes how equivalent-seats (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 Eq. (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 Eq. (12)

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

3.2. Route selection

Soyk et al. (2018)'s selection criteria for routes is applied. The city-pairs within the Southeast 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 h 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 this minimum threshold 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 operating under the 6th freedom traffic rights carry significant volumes of connecting passengers whose fares are either excluded or wrongly allocated (Tretheway, 2004) disrupt the data set.

OAG was used to retrieve scheduled data for the entire South-East Asian catchment market, where AirAsia X and Scoot operates. When the route selection criteria above is applied, the routes that filter through[4] are shown in Table 1 alongside their IATA code, airport-pair, airline type, and flight numbers for the years 2018 and 2019. Fig. 1 shows the routes of the two LHLCCs on a geographical map. Some insight on airline operations can be seen in Table 1. Flight capacity growth or shrinkage can be seen by comparing the 2018 flight frequencies to 2019. For example, in the SIN-PER city-pair, Scoot added 8 flights, Qantas Airways reduced their flights by 114, while Singapore Airlines remained the same. Throughout each city-pair, there are a mixture of airlines that do not change, increase or decrease their flight numbers. With regards to the LHLCCs in question, AirAsia X has only increased its flight numbers in the KUL-TYO market, and decreased flights in every other city-pair. Scoot increases its flights for its Australian (SIN-PER AND SIN-MEL) and Jeddah (SIN-JED) markets, but decreases its flights in every market it operates in. Reasons for such change are difficult to know since the rationale behind such strategic decisions are privy to the airlines making them. Reasons could cost optimisations, fleet optimisation, market reaction, etc.

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)[5] 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, Air Fares, Revenues, 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 that also incorporate direct bookings. 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 the world (Sabre, 2014; Bock et al., 2020; Suau-Sanchez et al., 2016; O'Connell et al., 2020).

Official Airline Guide (OAG)[6] is a subscription database that accounts for 96% of global passenger itineraries. Used in numerous studies (Lei and O'Connell, 2011; Pagliari and Graham, 2020; Corbet et al., 2019), it contains vast information (57 million flight status records updated yearly) on the schedules and capacity set by more than 980 airlines and 4000 airports. Finally, ITA Matrix Airfare Search provides a detailed breakdown of fare and tax cost between two airports.

The financial reports produced by airlines do not publish the individual components that make up ancillary revenues and it just gives an aggregated amount. However, a bespoke company by the name of IdeaWorks specialises in this area whose in-depth analytics were subsequently used. IdeaWorks estimated that the average ancillary revenue per passenger is $24 and a breakdown of ancillaries by airline was extracted.[7]

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 gathered in .CSV file format and a python script[8] 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. In total, the data sets amounted to around 74,000 rows

4. Results and discussion

4.1. City-pair REB

Fig. 2 shows the REB of all airlines grouped in their respective city-pairs with the city-pair REB means represented as horizontally-dotted

[4] Some city-pairs did not meet one of the criteria but were exceptionally included for their valuable insight. They are pointed out in Table 1.

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

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

[7] 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.

[8] Link to the script can be found here: https://github.com/AmrSol/REB.

Table 1
Directional routes selected for analysis (OAG, 2021).

#	City-pair	Carrier name	IATA code	Airport-pair	Type	Flights 2018	Flights 2019
1	SIN-PER[a]	Singapore Airlines	SQ	SIN-PER	FSNC	1460	1460
2		Qantas Airways	QF	SIN-PER	FSNC	495	391
3		Scoot	TR	SIN-PER	LHLC	373	381
4	KUL-PER[b]	Malaysia Airlines	MH	KUL-PER	FSNC	529	613
5		Malindo Airways	OD	KUL-PER	FSNC	645	723
6		AirAsia X	D7	KUL-PER	LHLC	433	409
7	SIN-MEL	Singapore Airlines	SQ	SIN-MEL	FSNC	1651	1694
8		Qantas Airways	QF	SIN-MEL	FSNC	657	708
9		Scoot	TR	SIN-MEL	LHLC	295	395
10		Emirates	EK	SIN-MEL	FSNC	365	365
11		Jetstar[c]	JQ	SIN-MEL	LHLC	132	95
12	SIN-SYD	Singapore Airlines	SQ	SIN-SYD	FSNC	1800	1825
13		Qantas Airways	QF	SIN-SYD	FSNC	724	750
14		Scoot	TR	SIN-SYD	LHLC	284	230
15		British Airways	BA	SIN-SYD	FSNC	365	364
16	KUL-SYD	Malaysia Airlines	MH	KUL-SYD	FSNC	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	FSNC	364	364
20		Air China	CA	KUL-PEK	FSNC	206	151
21	SIN-OSA	Singapore Airlines	SQ	SIN-KIX	FSNC	730	979
22		Scoot	TR	SIN-KIX	LHLC	209	189
23	KUL-OSA	Malaysia Airlines	MH	KUL-KIX	FSNC	359	402
24		AirAsia X	D7	KUL-KIX	LHLC	505	366
25	KUL-TYO	Malaysia Airlines	MH	KUL-NRT	FSNC	589	623
26		All Nippon Airways	NH	KUL-HND	FSNC	365	365
27		AirAsia X	D7	KUL-HND	LHLC	365	365
28		All Nippon Airways	NH	KUL-NRT	FSNC	365	365
29		Japan Airlines	JL	KUL-NRT	FSNC	365	365
30		AirAsia X[d]	D7	KUL-NRT	LHLC	0	24
31	KUL-JED	Saudi Arabian Airlines	SV	KUL-JED	FSNC	709	807
32		Malaysia Airlines	MH	KUL-JED	FSNC	256	169
33		AirAsia X	D7	KUL-JED	LHLC	158	199
34	SIN-JED	Saudi Arabian Airlines	SV	SIN-JED	FSNC	172	172
35		Scoot	TR	SIN-JED	LHLC	134	147

[a] SIN-PER has a flight time less than 6 h.
[b] KUL-PER has a flight time less than 6 h.
[c] Jetstar has less than 104 return flights in the year 2019.
[d] AirAsia X has had no flights in 2018 and was newly inaugurated in late 2019 with 24 flights.

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

lines for perspective on LHLCCs relative performance to FSNCs. The city-pair groups are arranged in ascending order according to their travel distance. Also, Yield per Passenger is plotted on the right y-axis to contrast yield performance with REB. LHLCCs are distinguished by their black colour, while FSNCs are grey.

There are a number of key findings. First, out of the eleven city-pairs, three have LHLCCs that operate at a greater than average level (KUL-TYO, SIN-MEL and SIN-JED), one at an average level (KUL-OSA), and the remainder below average. Second, there is no noticeable difference in REB performance between AirAsia X and Scoot; each have a mixture of city-pairs where they outperform and fall behind their competitors.

Third, it can be observed how LHLCCs achieve the lowest Yield in every city-pair. However, this does not correspond to a poor REB performance. The figure shows us that the REB difference between carriers is not as drastic as yield. For example, in KUL-TYO, AirAsia X (D7) has the lowest Yield per Passenger but has the second and third highest REB. As is the case in SIN-JED, Saudia Airline (SV) has a higher Yield per Passenger but the picture is reversed when viewing REB.

4.1.1. REB performance as a function of distance

Soyk et al. (2018) observed that LHLCCs on the North Atlantic performed better at shorter distances. With a city-pair range of 5550–8770 km, North Atlantic REB performance was above average up until 6200 km, and below average for further outlying city-pairs. This

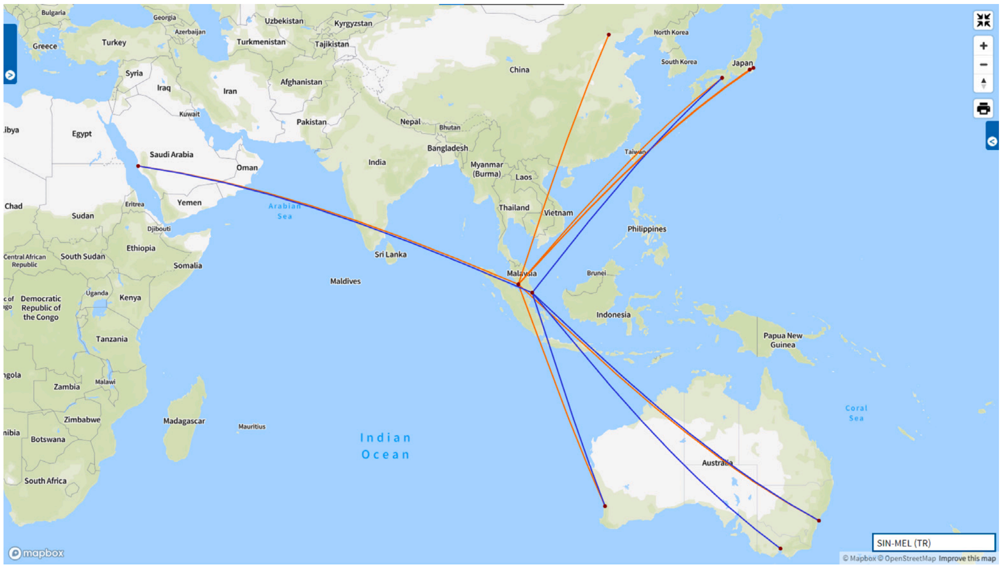

Fig. 1. LHLCC routes under investigation. AirAsia X in orange, Scoot in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Source: OAG.

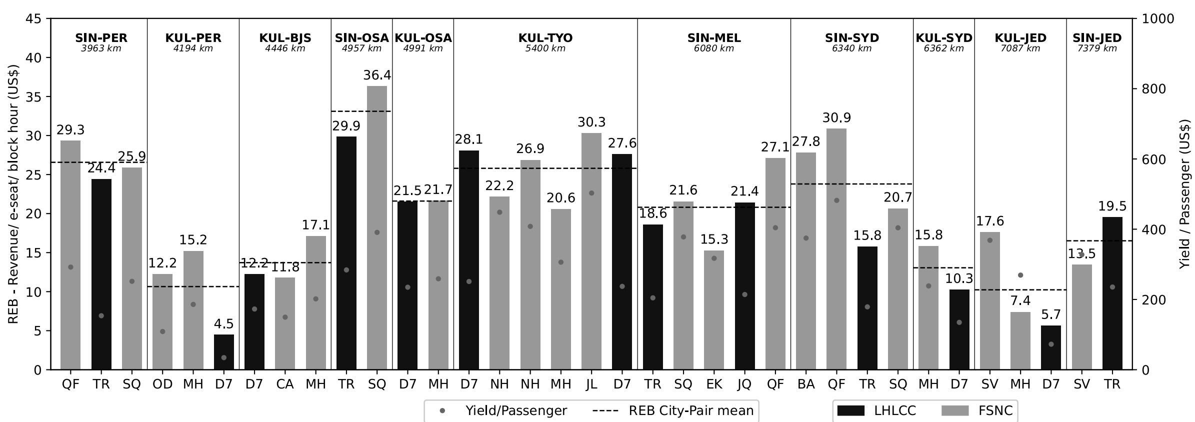

Fig. 2. REB values for airlines on different routes (QF - Qantas, TR - Scoot, SQ - Singapore Airlines, OD - Malindo Airways, MH - Malaysia Airlines, D7 - AirAsia X, CA - Air China, NH - All Nippon Airways, JL - Japan Airlines, EK - Emirates, JQ - Jetstar, BA - British Airways, SV - Saudi Arabian Airlines).

phenomenon could not be confirmed in the Southeast Asian market. This study examines city-pair at distances 3963–7379 km and finds city-pairs at distances less than 5550 km performing below average and city-pair distances above 6200 km performing above average. LHLCCs performing at an above average level is not a function of distance, rather it is an intricate balance of yield, load factors, and equivalent flight capacity. KUL-TYO and SIN-MEL have distances of 5400 km and 6080 km respectively and their LHLCCs are outperforming their FSNC counterpart. SIN-JED is the exception, being the farthest city-pair at 7379 km.

4.1.2. An analysis of AirAsia X and its competitors

Table 3 shows key variables extracted from the REB calculation process with alternating city-pairs greyed and the LHLCCs in bold. This table, alongside commercial analysis, will allows us to investigate and comprehend the findings represented by Fig. 2.

In KUL-PER, despite D7 achieving the highest passenger numbers its REB suffers from extremely low yields at around a quarter of what FSNCs are making, resulting in very low REB performance. Malaysia Airlines' (MH) high REB is attributed to its high yield passengers. In addition, in the peak holiday season where demand for leisure activity significantly increases, MH increased it capacity to facilitate high passenger movements (Hashim, 2019c). This is evident when viewing MH's equivalent flight capacity to D7's. The extra services were intended to give their passengers more flexibility when booking their travels and thus make their product more attractive. This is all in keeping with MH's plan to maximise its revenue and discontinue its loss making cycle. Its CEO, Izham Ismail, is focused on building yield, a goal that continues on from the former CEO who was focused on increasing load factors. MH's plan also includes pursuing growth in the Asia-Pacific market by deploying its A330 fleet on high-density routes across the region. Their aim is to "significantly improve the customer experience whilst also generating better revenue" (Chong, 2018). This plan can be seen bearing fruit with MH achieving the highest REB in both KUL-PER and in KUL-SYD.

With regards to KUL-BJS, MH has been focusing on gradually growing their Chinese market, one they categorise as "huge" alongside the Indian market (Chong, 2018; Ngai, 2019). They are seen to be successful in achieving high REB levels compared to Air China (CA) and D7 .

After seeing success in its KUL-HND route, AirAsia X planned to start a KUL-NRT service on 20 November 2019 (Hashim, 2019a). With only around fifty days of operation, AirAsia X generated the second highest REB in the city-pair. Their start date also explains why their passenger numbers are unusually low in Table 3.

Table 3
Key variable in REB analysis.

Origin Airport	Destination Airport	Airline	Passengers	Net yield (US$)	Revenue (US$)	E-seats	e	LF	RE	B	REB	Y/P/B
SIN	PER	QF	67,418	292.2	23,498,833	153,342	0.67	0.78	153.2	5.2	29.3	55.9
SIN	**PER**	**TR**	**126,744**	**153.7**	**17,131,482**	**135,681**	**0.89**	**0.92**	**126.3**	**5.2**	**24.4**	**29.8**
SIN	PER	SQ	303,369	251.7	85,398,934	633,260	0.70	0.76	134.9	5.2	25.9	48.4
KUL	PER	OD	90,093	108.7	10,436,345	148,241	0.84	0.77	70.4	5.8	12.2	18.9
KUL	PER	MH	72,809	185.9	15,329,109	177,708	0.75	0.63	86.3	5.7	15.2	32.8
KUL	**PER**	**D7**	**129,231**	**34.5**	**4,455,092**	**179,960**	**0.86**	**0.87**	**24.8**	**5.5**	**4.5**	**6.3**
KUL	**PEK**	**D7**	**73,100**	**172.8**	**12,686,877**	**160,600**	**0.86**	**0.54**	**79**	**6.5**	**12.2**	**26.8**
KUL	PEK	CA	13,055	149.6	3,778,466	49,960	0.74	0.64	75.6	6.4	11.8	23.3
KUL	PEK	MH	82,729	201.7	17,324,189	159,720	0.66	0.82	108.5	6.3	17.1	31.8
SIN	**KIX**	**TR**	**49,973**	**284.1**	**14,101,911**	**73,530**	**0.88**	**0.78**	**191.8**	**6.4**	**29.9**	**44.2**
SIN	KIX	SQ	264,294	391	108,305,345	459,141	0.71	0.85	235.9	6.5	36.4	60.3
KUL	**KIX**	**D7**	**96,259**	**234.9**	**22,846,080**	**161,040**	**0.86**	**0.71**	**141.9**	**6.6**	**21.5**	**35.6**
KUL	KIX	MH	88,418	258.9	24,098,261	176,880	0.65	0.81	136.2	6.3	21.7	41.2
KUL	**HND**	**D7**	**124,975**	**251.1**	**31,969,785**	**160,600**	**0.86**	**0.92**	**199.1**	**7.1**	**28.1**	**35.4**
KUL	HND	NH	47,325	448.4	23,550,418	153,300	0.57	0.60	153.6	6.9	22.2	64.7
KUL	NRT	NH	34,859	408	27,646,557	149,634	0.57	0.79	184.8	6.9	26.9	59.4
KUL	NRT	MH	147,502	306.2	48,722,821	338,135	0.62	0.76	144.1	7	20.6	43.8
KUL	NRT	JL	52,530	502.9	32,665,823	153,300	0.48	0.88	213.1	7	30.3	71.6
KUL	**NRT**	**D7**	**8,341**	**237.3**	**2,018,364**	**10,560**	**0.86**	**0.94**	**191.1**	**6.9**	**27.6**	**34.3**
SIN	**MEL**	**TR**	**108,062**	**204.6**	**22,689,065**	**160,284**	**0.89**	**0.76**	**141.6**	**7.6**	**18.6**	**26.9**
SIN	MEL	SQ	320,139	378	149,555,732	934,591	0.51	0.82	160	7.4	21.6	51
SIN	MEL	EK	40,838	317.1	22,800,273	204,992	0.64	0.54	111.2	7.3	15.3	43.6
SIN	**MEL**	**JQ**	**26,383**	**214.2**	**6,131,662**	**39,003**	**0.82**	**0.89**	**157.2**	**7.3**	**21.4**	**29.2**
SIN	MEL	QF	145,830	404.2	90,849,206	453,692	0.59	0.84	200.2	7.4	27.1	54.8
SIN	SYD	BA	51,285	374.7	34,530,740	160,160	0.68	0.85	215.6	7.8	27.8	48.4
SIN	SYD	QF	160,789	482	114,165,313	470,592	0.60	0.84	242.6	7.9	30.9	61.4
SIN	**SYD**	**TR**	**80,317**	**179**	**11,475,165**	**93,129**	**0.89**	**0.76**	**123.2**	**7.8**	**15.8**	**22.9**
SIN	SYD	SQ	395,690	404	196,718,710	1,224,940	0.50	0.80	160.6	7.8	20.7	52
KUL	SYD	MH	166,183	238.6	42,607,341	322,439	0.66	0.84	132.1	8.3	15.8	28.6
KUL	**SYD**	**D7**	**130,527**	**134.8**	**18,295,139**	**213,400**	**0.86**	**0.74**	**85.7**	**8.3**	**10.3**	**16.2**
KUL	JED	SV	68,349	368.5	54,186,850	356,610	0.73	0.57	151.9	8.6	17.6	42.7
KUL	JED	MH	35,930	269.3	7,358,265	104,751	0.64	0.45	70.2	9.5	7.4	28.5
KUL	**JED**	**D7**	**70,957**	**72.6**	**4,816,659**	**87,560**	**0.86**	**0.91**	**55**	**9.7**	**5.7**	**7.5**
SIN	JED	SV	21,559	327.6	8,721,588	72,240	0.71	0.54	120.7	8.9	13.5	36.6
SIN	**JED**	**TR**	**44,111**	**235.4**	**10,623,010**	**56,748**	**0.87**	**0.89**	**187.2**	**9.6**	**19.5**	**24.6**

For the KUL-JED market, Malaysia Airline's Project Amal, a pilgrim-based Airbus A380 operation, has been transporting religious pilgrims to Jeddah since October 2018 (Hashim, 2019b). The reason behind its low yields and REB is MH's charitable aim to offer cheap flights to pilgrims to perform their religious acts at a low cost.

4.1.3. An analysis of scoot and its competitors

Scoot (TR) is long-haul low-cost subsidiary of Singapore Airlines (SQ). Together they make the Singapore Airlines (SIA) Group. It is evident from Table 3 that SIA are capturing the majority of passengers and revenue of every city-pair they operate in. An SIA Group dominance is emerging from the results. As the group is further analysed, it can be seen in Fig. 2 that TR does not generate more REB than SQ in any city-pair where they both operate. This is due to consistently higher yields and passengers compared to TR.

Starting with SIN-PER, strong FSNC performance from SIA's competitor Qantas (QF), can be attributed to strong performance on the Perth to London route via Singapore in 2019 (Taylor, 2019) and their ability to capture high-yield passengers. QF has a firm grip on its home markets by capturing large numbers of the highest yield bearing passengers. Subsequently, their REB performance in SIN-PER, SIN-MEL, and SIN-SYD is the highest, as illustrated in Table 3, where it clearly shows that they have achieved the highest yield per passenger.

4.1.4. General observations

Table 3 reveals numerous observations. With regards to passengers, FSNCs competitors achieve the highest in every airport-pair with the exception of KUL-PER, KUL-KIX, KUL-HND, KUL-JED and SIN-JED. Malaysia is Perth's second largest visitor market, after the UK (CAPA). Narita International Airport offers greater capacity to airlines than Haneda airport, which is know for its saturated, limited and highly competitive slots. Although further from Tokyo city centre, Narita International's convenient public transportation allows it to be an attractive destination to price-sensitive passengers and high-yield passengers. AirAsia X can be seen to capitalise on this opportunity provided by Narita International and is generating above average revenue and REB. Once again, large passenger numbers are benefited from the JED destination because of religious travel, which is a segment that is highly influenced by low fare offerings.

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 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.

4.2. Average REB

When averaged across all airlines, results show that there is a 26.6% difference in overall REB between FSNCs and LHLCCs, as shown in Fig. 3. Overall, the FSNCs 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 in the research produced by Soyk et al. (2018). This is to be expected since the North Atlantic market is well established, lucrative, and enjoys a US-EU open-skies agreement where there are no restrictions on frequencies, air fares or capacity. Routes originating from London going to New York and Los Angeles are characterised with being large economies that are home to numerous Fortune 500 companies.

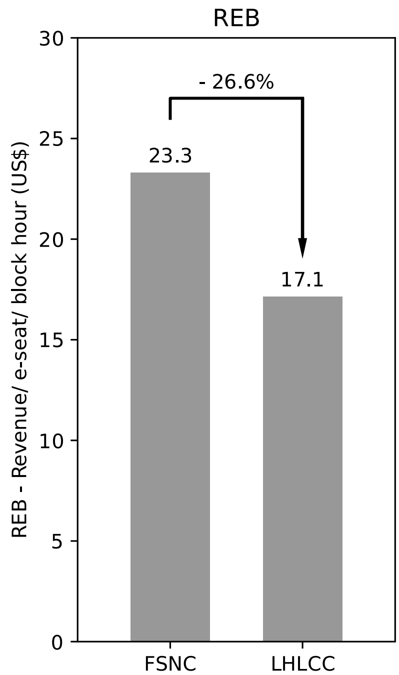

Fig. 3. Mean difference in REB for Southeast Asian.

4.3. Revenue and operating characteristics

Characterising revenue goes beyond summing up what the passengers pay the airline. Other factors are involved and are shown in Fig. 4. Fig. 4 shows revenue and operating characteristics influencing REB. The passenger weighted average of each value is calculated. When observing mean yield per passenger per block hour, LHLCCs generated 43.9% less than FSNCs. 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. LHLCCs aim for higher seat densities which does not allow them to have spacious premium seats. This is evident by LHLCCs having higher average seat densities at around 86.4% of their exit-limit; while FSNCs are at an average of 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 Southeast Asian market. LHLCCs carry significantly fewer connecting passengers and experience minimal revenue dilution when compared to FSNCs. LHLCCs in the Southeast Asian market also do 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 repeating 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. The results show that FSNCs have realised the benefits of ancillary revenues and are implementing it into their model. In Soyk et al. (2018), the difference in ancillaries was 646% rather than 30.6%. 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 long-haul low-cost passengers. Our assumption in this study are based on average ancillary revenues per passengers found in financial statements and reports, as mentioned in Section 3.3

4.4. Weaknesses

The exclusion of passengers with more than 1 stop, which account for around 10% of the passengers flying on the routes does not give the most accurate picture of activity in the market.

Block hours, B, when retrieved from OAG do not represent the actual block hours flown but the hours predicted by the airlines. Sabre MIDT does not have the capability to show actual block hours. Flight delays, or accelerated flight times are not known since they are retrieved from a Schedule database. Therefore, the true utilisation of the aircraft are unknown and could sway REB values in favour of LHLCCs if established, since LCCs aim to decrease turn around times.

5. Conclusion

Soyk et al. (2018)'s hypothesis holds true in the Southeast Asian long-haul low-cost market. However, his claim 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 Southeast Asian market. On a market level, the Atlantic has a difference of 4% while the difference for Southeast Asian is 26.6%. On a route level, both markets have shown LHLCC operations to be competitive. The key point is, despite drastically lower yields, LHLCCs, from an REB point of view, can be competitive. We learn that airlines can drive the airfare down while minimising the loss of revenue per flight capacity of the aircraft by adjusting for the numerous variables that directly impact it. REB does a great job of highlighting this phenomena. This metric also helps in the methodological advancement of airline performance analysis. Such a metric with its numerous variables, data requirements and processing is the next step for extremely insightful results.

This study quantitatively answers the four research questions and confirms the findings on the North Atlantic market (Soyk et al., 2018). The studies four key findings are as follows:

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, while 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 (Flight Global, 2002). In terms of deregulation, it will be a much more attractive market when the EU-ASEAN open skies agreement is finally enacted (Casey, 2020). The larger difference in REB between FSNCs and LHLCCs in the Southeast Asian market can be attributed

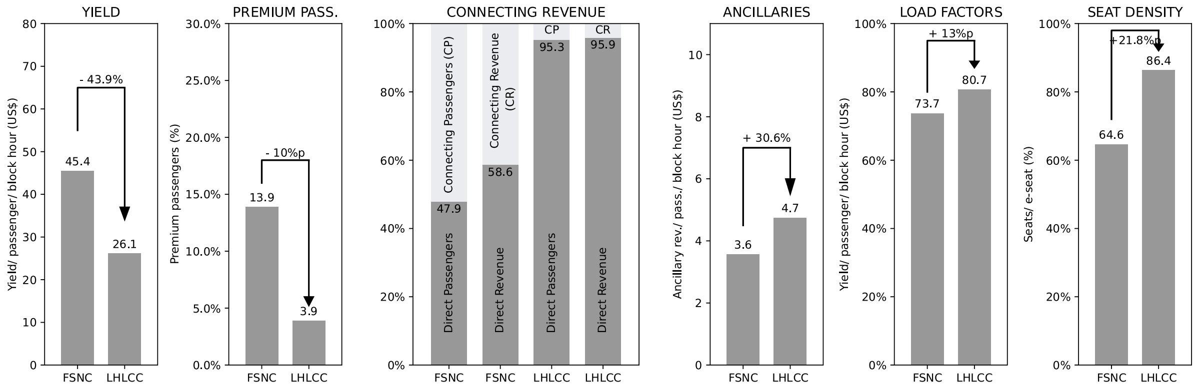

Fig. 4. Differences in revenue and operating characteristics influencing REB aggregated by carrier type, weighted by number of passengers.

to a lack of demand because of the constrained freedoms of the air. It appears that LHLCCs indeed do require a mature market for them to operate successfully or at least at a competitive level.

Future work would involve understanding to what degree can feeder traffic for LHLCCs be beneficial or harmful. Even though connecting passengers have revenue diluting effects that negatively affect REB, they increase load factors which in turn improve REB. Another area of research would be to quantify the number of self-connecting passengers and their subsequent effect on revenue performance.

All in all, there is much to learn about the long-haul low-cost model and the operating environment that it needs to thrive in. Soyk et al. (2018)'s new metric is a powerful addition to the arsenal of metrics used for analysis and it shines great light and deep insight on the inner workings of the long-haul low-cost model. It is hoped that more research goes into this financially distressed airline business model. It connects the opposite ends of the Earth and offers cost-effective solutions for people on a budget.

CRediT authorship contribution statement

Amr Soliman: Conceptualization, Methodology, Software, Validation, Investigation, Formal analysis, Data curation, Resources, Writing – original draft, Writing – review & editing, Visualization. **John Frankie O'Connell:** Conceptualization, Methodology, Validation, Formal Analysis, Data curation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Alireza Tamaddoni-Nezhad:** Conceptualization, Methodology, Validation, Investigation, Data curation, Visualization, Resources, Supervision, Project administration.

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