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Does asset-light strategy contribute to the dynamic efficiency of global airlines?

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ABSTRACT

This study analyses the effect of asset-light strategy on the dynamic efficiency of global airlines from 2008 to 2013. First, a dynamic data envelopment analysis is employed to estimate the dynamic efficiency of global airlines. Second, the degree of asset-lightness is computed by combining the concepts of the DuPont equation and financial ratios. Third, a multivariate analysis is performed to analyze the association between asset-light strategy and dynamic efficiency. The findings show that asset-light strategy significantly enables global airlines to have better corporate performance. Overall, this study suggests that global airlines should efficiently manage and allocate their light resources to sustain challenges in the dynamic global airline industry.

1. Introduction

The global airline industry incurred a $13 billion net loss in 2001 based on statistical data provided by the International Air Transport Association (IATA). Furthermore, global issues such as fluctuating international oil prices, the global economic recession, and contagious diseases have affected airline operations, including dismissals of staff or filings for bankruptcy protection. Although passenger and cargo demands have recovered in recent years, significant losses are still found in all regions, except for Asia-Pacific and Latin American emerging countries that have higher international passenger demands compared to North America and Europe. Different players have resulted in the evolution of competition in the global airline industry and recent developments in the industry include changing business models. Southwest Airlines has differentiated itself as a low-cost, short-haul, express airline, and that has proven to be a winning strategy for competing in the highly competitive airline industry.

Besides the above-mentioned scenario, this study analyzes how well airlines perform in the global market in terms of continuously managing and allocating resources to ensure their survival and growth. In other words, global airlines should have lower operating costs and risks in the continuing evolution of the highly competitive global airline industry (Belobaba and Odoni, 2009). A sustainable competitive advantage can lead to an above-average performance or profits (Barney, 1991; Wiggins and Ruefli, 2002). Limited resources available include both tangible and intangible assets, both of which can be identified from airlines' financial statements such as patents, franchises, trademarks and copyrights, and strategic intangible resources that are not captured on airlines' financial statements, such as corporate branding, customer relationships, and operating strategies (Liou, 2011).

A type of corporate strategy that could create a competitive advantage is the asset-light strategy, which corporations have been utilizing over the past few decades (Gannon et al., 2010) as a response to serious challenges in the dynamic airline market. In

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other words, taking full advantage of limited resources should be the main goal of global airlines, because efficient management of limited resources means better performance. In literature, a few studies have considered how the asset-light strategy affects corporate performance in various industries. The asset-light strategy has been shown to create values in international hotel corporations (Gannon et al., 2010), generate a competitive advantage in the telecommunications industry (Liou, 2011), and improve corporate performance in the semiconductor industry (Wen et al., 2012). The aforementioned studies show that limited resources can be in intangible, which can create a competitive advantage and ultimately better corporate performance.

In the airline industry, Broderick (2015) reported that airlines are reshaping their business model by engaging in asset-light strategy. As discussed earlier, global airlines should find ways to lower their operating costs and risks, and also increase their efficiency by utilizing their limited resources (including aircraft and staff), all of which will ultimately reduce their profit volatility and improve their profitability. To comprehensively understand the effect of the asset-light strategy on corporate performance in the airline industry, we argue that a longitudinal and multidimensional measure of corporate performance measure should be applied. Extant studies on performance measure have primarily examined the return on assets and/or Tobin's Q, which are uni-dimensional (McWilliams and Siegel, 2000; Surroca et al., 2010). A robust methodology for this study is data envelopment analysis (DEA) (Bowlin, 1995) for the following reasons: first, DEA is able to not only simultaneously evaluate numerous variables, but also account for possible interactions among the variables. Second, DEA can determine optimal efficiency and relative efficiency as captured by variables (Narimani and Narimani, 2012). Third, DEA provides value-added facts and figures at a better picture than financial ratios do (Feroz et al., 2003).

With respect to performance measure, Tone and Tsutsui (2010) indicate that long-term investments are normally found in the actual business world. Long-term investments are particularly observable in the airline industry, which have large quantities of capital investments. Specifically, carry-over activities take place between two periods of time. This viewpoint is also supported by the longitudinal view of accounting, which accounts for assets and liabilities are amassed and brought forward for an indefinite time period. In the past, researchers normally use window analysis (Webb, 2003; Yang and Chang, 2009) and the Malmquist index (Asmild et al., 2004; Uri, 2000) to gauge efficiency changes for two periods. However, the aforementioned DEA models ignore carry-over activities. Following Lu et al. (2014), we thus employ a dynamic DEA approach to estimate the dynamic efficiency of global airlines over a long-term period. In short, we provide a holistic view of the efficiency of global airlines from a long-term perspective.[1]

We next regress the asset-light strategy on the dynamic performance in an ordinary least square model for the period from 2009 to 2013. Consistent with the study by Liou (2011), the asset-light strategy is measured as the degree of asset-lightness (DAL), which represents light resources or intangible assets. In summary, we contribute to the available literature by focusing primarily on extending prior research on the use of the asset-light strategy in the airline industry.

The remainder of this paper proceeds as follows: prior studies are documented in Section 2, the next section describes the research method and data collection of this study. The empirical results are presented in Section 4, while this study is wrapped up in Section 5.

2. Literature review

2.1. The asset-light strategy

Two major classifications of assets are heavy assets and light assets (Liou, 2011), whereby heavy assets (a.k.a. tangible assets) are usually reported in a corporate annual report. A non-exhaustive examples of light assets, which might be commonly known as intangible assets, include goodwill, patents, franchises, trademarks and copyrights and exclude certain key substances such as corporate strategies, ranging from marketing ability to efficiency in resource management (Amit and Schoemaker, 1993), all of which reflect exceptionally unique abilities that can possibly be imitated in an imperfect way because there are no substitutes, and have unique abilities (Wernerfelt, 1984).

Specifically, the asset-light strategy deals with minimal physical resources in maximizing corporate performance. Based on the resource-based view, strategic resources controlled by companies are important factors that create competitive advantages (Barney, 1991). There are two assumptions at play. The first assumption is that the resources owned by companies are heterogeneous, which means that a company gains competitive advantage by owning specific resources that others lack. The second assumption is that resources cannot flow among companies, leading to maintaining heterogeneity.

To quantify the asset-light strategy, a researcher can use one of the two indicators (Liou, 2011): the dollar value of light assets and the degree of asset-lightness in ratio.[2] The latter is a measure of a company's ability in using physical resources to create intangible values. Overall, companies should emphasize their light assets as key resources to generate and sustain competitive advantages, and ultimately to enhance firm value.

The impact of the asset-light strategy on various industries has been discussed widely in the literature. For an example, Sohn et al. (2013) examine the theoretical and empirical effectiveness of the strategy in the U.S. hotels and motels industry. The results indicate that expanding fee business and decreasing fixed asset intensity have a positive impact upon firm value. Liou (2011) reveals the influence of asset-light operations on competitive advantages on the telephone communications industry in Taiwan. Moreover, Ghazvini et al. (2015) propose that firms with light tangible assets, such as distributed generation units and energy storage systems, can survive longer in a competitive retail electricity market. The study further explains that with asset-light strategy, the retail electricity providers are able to reduce the risk of financial losses in the firms.

2.2. The impact of the asset-light strategy on corporate performance

Performance evaluation is one of the important topics for company stakeholders, because it articulates the corporate value that reflects not only the current state of operation, but also future potential growth. In other words, performance evaluation is beneficial to the continuous growth of companies (Achterbergh et al., 2003). To measure corporate performance, prior studies have utilized accounting-based measures such as return on equity

[1] Some might argue that airlines are more efficient airlines if they are able to deliver lower costs per seat in competing to sell seats on flights.

[2] Readers are encourage to scrutinize Liou, F.-M., 2011. The effects of asset-light strategy on competitive advantage in the telephone communications industry. Technology Analysis & Strategic Management 23, 951–967. For the theoretical framework behind the asset-light strategy.

(Wan, 1998), return on sales (Geringer et al., 2000), return on invested capital (Liou, 2011), and return on total assets. For example (Hawawini et al., 2003), examined corporate performance by adopting accounting-based and value-based measures, and they indicated that most value-based measures are more able to reveal value creations. Furthermore, McConnell and Servaes (1990) emphasize that Tobin's Q is a widely accepted measure of corporate performance, as the firm value is measured from both the market value and book value perspective. The higher a firm's Tobin's Q, the more effective are the firm's governance mechanisms (McKnight and Weir, 2009).

Using return on invested capital to measure competitive advantage, Liou (2011) shows that the asset-light strategy results in greater return on invested capital, suggesting competitive advantages for companies in the telecommunications industry. Subsequently, Wen et al. (2012) apply the same concept to examine the impact of the asset-light strategy on the sustainable competitive advantage of companies in the Japanese semiconductor industry. In other words, the authors show that an increasing number of semiconductor companies achieve improved firm performance by implementing the asset-light strategy alongside investments in physical capital. Using international hotel corporations, Gannon et al. (2010) find that the asset-light strategy contributes to human resource management practices, including valuable opportunities. In conclusion, extant literature shows that the asset-light strategy positively affects firm performance.

2.3. Airline DEA studies

Many recent studies have employed the DEA method to assess the efficiency of the airline industry worldwide. Various output and input sets have been used to measure efficiency. For examples, Lu et al. (2012) employ input variables like fuel consumed and seating capacity, and output variables like revenue passenger miles and non-passenger revenue. However, Barros et al. (2013) use total costs and total employees as inputs and total revenue as outputs. In the U.S., Mallikarjun (2015) applies the non-oriented DEA network methodology to identify the sources of its inefficiency. The findings suggests that major US airlines are more efficient than national US airlines in spending operating expenses and gaining operating revenue, but there is no significant difference in their service supply and demand efficiencies. Similarly, Cui and Li (2015) explain that capital efficiency is an important factor in driving energy efficiency. The result is concluded based on a new model, Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA) and Spearman correlation coefficient is applied to validate the applicability of the new model.

Furthermore, Gomes Júnior et al. (2015) use the DEA approach to evaluate the operational performance of Brazilian airlines. The study employs a non-radial efficiency measure based on vector concepts that considers each efficient airline as a real target at once, and the results indicate a large number of negative efficiency scores for most inefficient airlines in Brazil. Arjomandi and Seufert (2014) apply bootstrapped DEA models to examine both the environmental and technical efficiencies of 48 of the world's major full-service and low-cost carriers from the International Air Transport Association (IATA) over the period 2007–2010. The findings conclude that the operations of low-cost carriers are technically operating under increasing returns to scale. In Europe, Duygun et al. (2016) apply the network DEA approach to test the efficiency level of European airline industry. Consistently, in general, most of the inefficiencies are generated in the first stage of the analysis. Oum et al. (2013) evaluate the social efficiency of railway firms and airlines in Japan. The study incorporates government spending on air infrastructure and life-cycle CO2 emissions as inputs and outputs, respectively. The nonparametric directional output distance function (DODF) results indicate that the railroads are more socially efficient than airlines in Japan's domestic intercity travel market during 1999–2007.

Moreover, prior studies have examined the importance of various aspects on the efficiency of airlines. Chang et al. (2014) extend the DEA model by including the environmental slack-based measurement to assess the airline's efficiency. They argue that the main reason of economic and environmental inefficiency in airlines is caused by the poor fuel consumption. Wang et al. (2011) employ the traditional DEA method and indicate that board governance is proven to be significantly related to technical efficiency. Consistently, Saranga and Nagpal (2016) apply the traditional DEA method to examine the relationship between various performance drivers, operational efficiencies for all the Indian airlines for the period 2005 to 2012. The findings suggest that structural and regulatory are factors that drive operational efficiencies and they enhance market performance. Furthermore, Merkert and Hensher (2011) apply a two-stage DEA and conclude that successful strategic management has significant impacts on airline efficiency from technical, allocative and cost perspective for the 58 largest passenger airlines.

Additionally, Wanke and Barros (2016) use the Virtual Frontier Dynamic Range Adjusted Model - DEA to examine the efficiency of Latin American airlines. They conclude that the impact of fleet mix and public ownership cannot be overlooked in Latin American airlines. Interestingly, Merkert and Pearson (2015) examine the efficiency level of the airline industry from the customer service perspective. The study employs DEA models and second-stage truncated regressions for efficiency measurement. The result concludes that only the cabin crew have a significant impact on the overall airline efficiency. Other than that, Merkert and Williams (2013) investigate the use of public service obligations contracts and its impact on the European airline efficiency by applying a two-stage DEA approach. Most recently, See and Rashid (2016) employ the traditional DEA method and assess the impact of privatization on the total factor productivity growth of Malaysia Airlines over a 34-year period.

In summary: First, numerous research has been carried out to evaluate the efficiency level of the airline industry by employing the DEA method. However, the empirical significance of these studies remains largely unknown, especially in terms of dynamic DEA approach. The dynamic slacks-based measure (DSBM) model (Tone and Tsutsui, 2010) enables us to estimate periodic efficiency in a specific period from the longitudinal view of corporate production process, all of which are advantages over traditional DEA models. Therefore, we apply the DSBM model to gauge the efficiency of airlines. Second, there are few studies that measure the degree of asset-lightness by combining the concepts of the DuPont equation and financial ratios, particularly by regressing the asset-light strategy on the dynamic performance. This paper seeks to fill the gap.

3. Research methodology

3.1. Longitudinal view of corporate production process

The income statements and balance sheets produced by companies reflect their financial activities and positions. From the accounting perspective, companies complete their annual accounting cycles by reporting earnings after taxes (total revenues minus total expenditures), and assets, liabilities and equities. The former compiles items in the income statements that are considered to be temporary accounts, while the latter accumulates long-term account balances in the balance sheets that are known as permanent accounts. With respect to the longitudinal view of corporate production process, we highlight the long-term account balances that are carried over from a financial year to another. In this study, we name this type of items as carry-overs. To give a better picture of the dynamic production process, we present Fig. 1 to depict that of an airline company.

In Fig. 1, carry-overs include balance-sheet items like equities, liabilities and intangible assets, all of which are accumulated over period, for e.g. from t to t+1. Equities and liabilities are treated as input carry-overs, while intangible assets are considered as output carry-overs. As for the other variables: input – operating expenses, and output – revenue and market value are all only for a current year. Definitions of the variables are as follows. Liabilities$_{t-1}$ are the sum of current liabilities and non-current liabilities in the previous year. Equities$_{t-1}$ are the total number of shares outstanding held by common and preferred shareholders in the previous year. Operating expenses consist of selling expenses, general and admin expenses and advertising expenses in the current year. Intangible assets are goodwill, patents, franchises, trademarks and copyrights in the current year. Revenue refers to the gross sales income in the current year. Market value is the multiplication of the number of shares outstanding and the year-end share price in the current year. Overall, we measure airline efficiency by assuming that airlines use an input, two input carry-overs to produce two outputs and one output carry-over. This concept of a longitudinal view of corporate production process is consistent with prior studies in various industries (for examples, Kweh et al., 2014a; Kweh et al., 2014b; Lu et al., 2014; Wang et al., 2014).

3.2. Sample selection and data sources

We extract relevant financial data from the COMPUSTAT database and also hand collect some data from the annual reports on Form 10-K and websites of our sample. We define airlines as companies with a Standard Industrial Code (SIC) of 451 or 452, whereby 60 airlines are available in the COMPUSTAT database after 2008. To have the highest possible number of airlines for the analysis purpose, we choose a six year sample period from 2008 to 2013. In the data screening process, we eliminate 11 airlines due to missing and unavailable data; therefore, we have a final sample of 49 airlines, and there are 294 firm-year observations from this

Table 1
Summary statistics of the 49 airlines companies.

	Mean	St Dev.	Min.	Max.
Panel A: Year 2008				
Liabilities$_{t-1}$	16,330.49	31,970.87	4.18	123,604.44
Equities$_{t-1}$	8834.07	25,493.56	1.07	153,236.58
Operating expenses	17,312.86	32,911.45	13.89	146,153.69
Intangible assets	618.47	1857.76	0.26	10,879.24
Revenue	18,425.06	35,363.52	14.61	175,959.27
Market value	70,154.13	328,417.06	0.69	2,195,991.37
Panel B: Year 2009				
Liabilities$_{t-1}$	17,531.44	33,156.53	6.92	131,863.88
Equities$_{t-1}$	9635.21	25,976.51	1.35	145,464.10
Operating expenses	14,447.71	25,550.34	5.26	117,369.00
Intangible assets	601.36	1788.81	0.00	11,246.70
Revenue	16,392.89	29,451.37	5.99	137,238.81
Market value	75,334.55	329,822.47	0.33	2,226,737.04
Panel C: Year 2010				
Liabilities$_{t-1}$	18,162.59	33,547.82	5.78	125,069.03
Equities$_{t-1}$	12,018.30	31,262.51	2.93	174,714.10
Operating expenses	18,003.60	31,849.37	5.97	141,074.85
Intangible assets	594.52	1740.66	0.29	10,646.12
Revenue	21,384.59	38,998.46	7.21	178,655.00
Market value	158,598.33	874,078.86	1.62	6,114,178.81
Panel D: Year 2011				
Liabilities$_{t-1}$	18,958.07	34,008.43	5.50	141,264.52
Equities$_{t-1}$	11,791.09	29,001.29	3.10	166,324.83
Operating expenses	21,241.36	37,605.09	7.00	167,679.33
Intangible assets	635.27	1786.15	2.08	11,143.46
Revenue	23,662.83	42,412.14	8.03	191,665.58
Market value	129,194.29	621,060.74	2.41	4,253,787.57
Panel E: Year 2012				
Liabilities$_{t-1}$	20,982.43	38,395.51	5.14	166,026.34
Equities$_{t-1}$	11,995.65	28,018.50	3.25	152,014.51
Operating expenses	22,343.03	38,668.83	6.80	153,138.54
Intangible assets	715.99	1948.07	0.25	12,467.39
Revenue	24,776.03	43,087.31	7.98	175,139.11
Market value	115,664.64	618,153.05	3.51	4,299,323.63
Panel E: Year 2013				
Liabilities$_{t-1}$	22,782.66	43,526.07	4.67	202,486.02
Equities$_{t-1}$	11,361.20	25,694.52	3.32	125,753.39
Operating expenses	20,914.10	36,572.36	6.51	137,139.43
Intangible assets	807.64	2115.08	0.22	13,536.56
Revenue	23,394.69	40,971.66	7.88	156,181.26
Market value	99,733.20	497,382.14	7.56	3,420,815.35

Note: The unit for the variables is 1 million U.S. dollars.

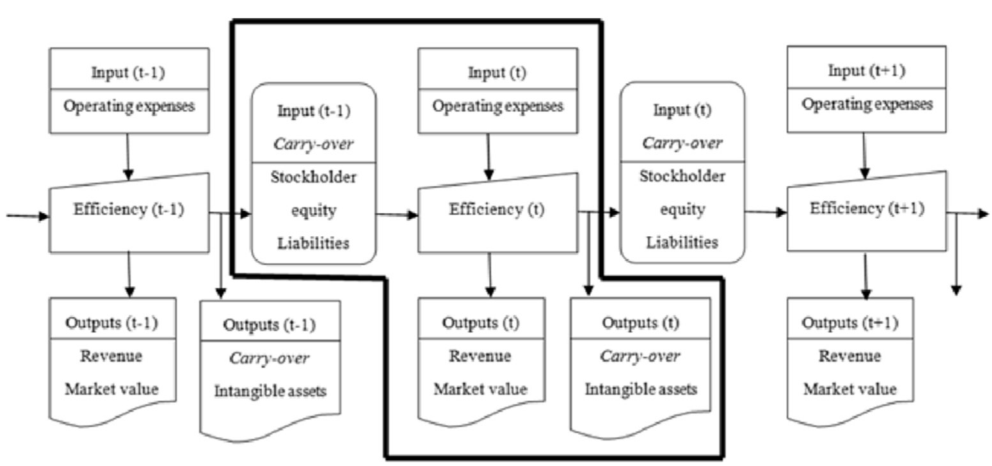

Fig. 1. Dynamic production process for airline companies.

sample period. These airlines' total revenues account for more than three-fourth of the total revenues of all 60 global airlines. See Appendix I for the list of airlines involved in this study.

Table 1 reports the summary statistics of the 49 airlines for the period 2008–2013. The results show that the input carry-overs increase almost monotonically over the sample period. However, the output carry-overs decrease from USD 618.47 million in 2008 to USD 594.52 million in 2010 and increase to USD 807.64 million in 2013. The input and outputs fluctuate over the sample period. These observations in some ways justify the necessity to explore whether or not airlines efficiently use their current and long-term resources to generate the maximum possible outputs in a relative basis.

In addition, we also check whether the DEA model of this study meets the requirement stipulated by Golany and Roll (1989), particularly the ratio of the number of decision-making units (DMUs) to the number of all DEA variables. In this study, the ratio of airlines (49 companies) to the DEA variables used (six variables) is about 8.2, which is more than four times greater than the conventional requirement. In addition, we examine the correlations among the inputs, carry-overs and outputs. The results in Table 2 indicate that all DEA variables used in this study are positively and significantly correlated. Overall, these reflections suggest that the developed dynamic production process of this study is valid.

$$ATE_0^* = \min \frac{(1/T)\sum_{t=1}^{T}\left[1 - \frac{1}{(m+nbad)}\left[\sum_{i=1}^{m}\left(s_{it}^{-}/x_{iot}\right) + \sum_{h=1}^{nbad}\left(s_{ht}^{bad}\Big/z_{hot}^{bad}\right)\right]\right]}{(1/T)\sum_{t=1}^{T}\left[1 + (1/s)\sum_{r=1}^{s}\left(s_{rt}^{+}/y_{rot}\right)\right]} \quad (1)$$

3.3. Dynamic DEA method

In the DEA literature, the dynamic slacks-based measure (DSBM) model (Tone and Tsutsui, 2010), a dynamic DEA model that not only considers the time-change effect over periods, but also accounts for carry-overs between two consecutive periods, is available for use. The DSBM model also enables us to estimate periodic efficiency in a specific period from the longitudinal view of corporate production process, all of which are advantages over traditional DEA models. Therefore, we apply the DSBM model to gauge the efficiency of airlines.

With respect to carry-overs, we follow the model of Tone and Tsutsui (2010) to use desirable (good) links (the carry-overs) and undesirable (bad) links, in which the former is viewed as output carry-overs (intangible assets in this study) and the latter is meant for input carry-overs (equities and liabilities in this study). The values of good links should be more than the observed values, with a relative shortage of this type of links being considered as not efficient. Meanwhile, the values of bad links should be less than the observed values, with a relative excess of this type of links being regarded as not efficient.

Recall the dynamic production process presented in Fig. 1 and assume that it deals with $nDMUs$ $(j = 1, ..., n\ )$ over T terms $(t = 1, ..., T)$. At each term, $DMUs$ have m common inputs $(i = 1, ..., m)$ and s common outputs $(r = 1, ..., s)$. Let x_{ijt} and y_{rjt} denote the input and output values of DMU_j at term t, respectively. This study denotes the category link as z^{bad}. In order to assess the dynamic production process in term t, DMU_j and item i this study employs, for example, the notion $z_{hjt}^{bad}(h = 1, ..., nbad; j = 1, ..., n; t = 1, ..., T)$ to denote bad link values, where $nbad$ is the number of bad links. These are all observed values up to term T. By using these expressions for production, this study expresses observed DMU_o $(o = 1, ..., n)$. Therefore, this study defines non-oriented efficiency by solving the following:

S.T.

$$x_{iot} = \sum_{j=1}^{n} X_{ijt}\lambda_j^t + s_{it}^{-}, \quad (i = 1, ..., m; t = 1, ...T), \quad (2)$$

$$y_{rot} = \sum_{j=1}^{n} y_{rjt}\lambda_j^t - s_{rt}^{+}, \quad (r = 1, ..., s; t = 1, ..., T), \quad (3)$$

$$z_{hot}^{bad} = \sum_{j=1}^{n} z_{hjt}^{bad}\lambda_j^t + s_{ht}^{bad}, \quad (h = 1, ..., nbad; t = 1, ..., T), \quad (4)$$

$$\sum_{j=1}^{n} z_{hjt}\lambda_j^t = \sum_{j=1}^{n} z_{hjt}\lambda_j^{t+1}, \quad (\forall h; t = 1, ..., T-1), \quad (5)$$

$$\sum_{j=1}^{n} \lambda_j^t = 1, \quad (t = 1, ..., T), \quad (6)$$

$$\lambda_j^t \geq 0, s_{it}^{-} \geq 0, s_{rt}^{+} \geq 0, s_{ht}^{bad} \geq 0. \quad (7)$$

where s_{it}^{-}, s_{rt}^{+}, and s_{ht}^{bad} are slack variables denoting, respectively,

Table 2
Pearson correlation coefficients for inputs and outputs.

	Liabilities_{t-1}	$\text{Stockholder equity}_{t-1}$	Operating expenses	Intangible assets	Revenue	Market value
Liabilities_{t-1}	1.000					
$\text{Stockholder equity}_{t-1}$	0.646	1.000				
Operating expenses	0.920	0.845	1.000			
Intangible assets	0.544	0.411	0.532	1.000		
Revenue	0.927	0.849	0.997	0.530	1.000	
Market value	0.017	0.005	0.021	−0.003	0.021	1.000

Note: All coefficients are significant at the one percent level.

input excess, output shortfall, and link excess.

As documented by Tone (2001), this objective function is an extension of the non-oriented SBM model and deals with excesses in both input resources and undesirable (bad) links. The numerator is average input efficiency, and the denominator is the inverse of the average output efficiency. We define non-oriented overall efficiency as their ratio, which ranges between 0 and 1, and is 1 when all slacks are zero. This objective function value is also unit-invariant.

The production possibility set for the objective DMU_O $(o = 1, \ldots, n)$ is expressed by (2)–(7). Let an optimal solution (1) subject to (2)–(7) be:

$$\left\{\lambda_j^{t*},\ j = 1, 2, \ldots, n;\ s_{it}^{-*}, i = 1, \ldots, m;\ s_{rt}^{+*}, r = 1, \ldots, s; s_{ht}^{bad*}, h = 1, \ldots, nbad,\ \ t = 1, \ldots, T\right\}.$$

If the optimal solution for (1) $ATE_0^* = 1$, then the target DMU is said to be non-oriented overall efficient or briefly overall efficient. If all optimal solutions of (1) satisfy $TE_{ot} = 1$, then the target DMU is said to be non-oriented term efficient or, briefly, term efficient for term t. This implies that the optimal slacks for term t in (8) are all zero.

$$TE_{ot}^* = \frac{1 - \left[\frac{1}{(m+nbad)}\left(\sum_{i=1}^{m}\left(s_{it}^{-*}/x_{iot}\right) + \sum_{h=1}^{nbad}\left(s_{ht}^{bad*}\Big/z_{hot}^{bad}\right)\right)\right]}{1 + (1/s)\sum_{r=1}^{s}\left(s_{rt}^{+*}/y_{rot}\right)},\ t = 1, \ldots, T. \tag{8}$$

3.4. Measures of the asset-light strategy

A company is said to have earned an abnormal return if its excess return is higher than its opportunity cost of resources used. Revenues or returns provide a market measurement of outputs because returns made are the minimum value perceived by its customers in a competitive market. The proxy of the asset-light strategy in this study is derived based on the concepts of the DuPont equation and financial ratios, consistent with Tang and Liou (2010). The following equations summarize the steps to gauge the degree of asset-lightness (*DAL*), with the first being return on invested capital (*ROIC*):

$$ROIC = \frac{NOPLAT}{IC} \tag{9}$$

where *NOPLAT* is the multiplication of earnings before interests & taxes and $(1 - Tax)$, plus deferred income tax (if available), *Tax* is tax expense divided by pre-tax income, and *IC* is the summation of net fixed assets, net working capital and other assets. Unlike other ratios such as P/E ratio and return on equities, *ROIC* is a measure of the book rate of return by considering debt and the actual invested capital. *ROIC* is used because it reflects not only earnings efficiency and managerial ability to improve shareholders' values (Cao et al., 2006), but also the existence and absence of a firm's competitive advantage (Tang and Liou, 2010). Next, weighted average cost of capital (*WACC*), which is the least possible return that should be made by a company on its invested capital, is shown as follows.

$$WACC = \frac{D}{D+E} \times R_d \times (1 - Tax) + \frac{E}{D+E} \times R_e \tag{10}$$

where the cost of debt (R_d) is interest expense divided by total debts, the cost of equity (R_e) is the summation of risk-free rate of return and the multiplication of beta and risk premium. A firm is considered as performing well if its *ROIC* is higher than its *WACC* and vice versa. In other words, *WACC* reveals capital risks in the efficient market.

To make returns on its invested capital, a firm can invest in heavy (physical) or light (intangible) assets, which will result in a *ROIC* that is greater than the firm's costs plus the risk-free rate of return (Liou, 2011). Therefore, measuring a firm's value based on excess return implies that the firm's value should be greater than the book value of deposits that earn risk-free rate of return (Liou, 2011). We present the association between *ROIC* and *WACC*, incorporating the risk-free rate of return (r) in Equation (11) as follows.

$$\frac{ICA}{(ROIC - WACC)} \geq \frac{ICB}{r} \tag{11}$$

where *ICA* is the real value of the assets utilized and *ICB* is the book value of the assets utilized, which is calculated as the difference between total assets and intangible assets. Equation (12), rearranged from Equation (11), can be used to derive *ICA*:

$$ICA \geq \left(\frac{ROIC - WACC}{r}\right) \times ICB \tag{12}$$

which is equally the same as Equation (13).

$$ICA \geq \frac{1}{r} \times ICB \times (ROIC - WACC) \tag{13}$$

From Equations (12) and (13), we can infer that the real value of the invested resources increases with the ratio of excess return $(ROIC - WACC)$ to the risk-free rate of return (r). Equation (14) gives the lower bound for superior performance:

$$ICA - ICB = \frac{1}{r} \times ICB \times (ROIC - WACC) - ICB \tag{14}$$

The difference between the real value (*ICA*) and the book value (*ICB*) in Equation (14) is defined as the off-balance-sheet light assets, or in other words the excess benefits generated by the *ICA* over the *ICB*. Rewriting Equation (14), we derive an asset-light valuation model as follows:

$$LA = ICA - ICB = \frac{ICB \times (ROIC - WACC - r)}{r} \tag{15}$$

Equations (14) and (15) reveal that the remainder of *ICA* over *ICB* is the excess returns. Next, we add reported goodwill and intangible assets on balance sheets (i.e., patent, franchise and trademark) into Equation (15) to derive Equation (16):

Table 3
The dynamic DEA results statistical analysis.

Total sample	2008	2009	2010	2011	2012	2013	Overall mean
Mean (N = 49)	0.526	0.621	0.625	0.645	0.627	0.584	0.605
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Min	0.000	0.001	0.001	0.001	0.001	0.000	0.000
St Dev	0.473	0.459	0.449	0.440	0.456	0.468	0.473

$$LA = \frac{1}{r} \times ICB \times (ROIC - WACC - r) + GW + IA \quad (16)$$

where LA is the value of light assets. The term $(ROIC - WACC - r)$ is the rate of return on light assets. To be exact, the degree of asset-lightness (DAL) is the ratio of LA to ICB, as shown in Equation (17).

$$DAL = \frac{LA}{ICB} \quad (17)$$

4. Statistical findings

4.1. Dynamic performance of airlines and their characteristics

Table 3 shows the average efficiency outcomes of the airlines over the sample period. The efficiency scores increase from 0.526 in 2008 to 0.645 in 2011, and then decrease from thereafter (2013 mean value = 0.584). The lowest efficiency score in 2008 can be linked to the 2007–2008 global financial crisis that caused global financial collapses and soaring oil prices, which in turn caused most airlines' performance to suffer. However, with the global economic recovery beginning in mid-2009, revenue and earnings are beginning to rebound sharply.

It is expected that the efficiency of companies employing the asset-light strategy will be higher compared to their counterparts who use more traditional methods. Therefore, we examine the impact of DAL on the dynamic efficiency of airline companies, linking two main operating characteristics including leverage (LEV) – the ratio of total liabilities to total assets, and firm risk ($RISK$) – the ratio of long-term debt to total assets. These operating characteristics are then classified into three categories: high scope, middle scope and low scope for further analyses.[3] The Kruskal–Wallis test (a non-parametric test of difference) is used for unknown distribution scores (Sueyoshi and Aoki, 2001). The non-parametric statistical analyses for the two operating characteristics are presented in Tables 4 and 5.

In Table 4, we divide LEV into three categories: high scope, middle scope and low scope. The low group consisted of those companies with a mean of LEV smaller than 0.6 between 2008 and 2013. The high group consisted of those companies with a mean of LEV bigger than 0.75 between 2008 and 2013. The Kruskal–Wallis test results are also shown in Table 4. The results in Panel B of Table 4 indicate that the low group companies' DAL is higher than the high group companies' DAL from 2008 to 2013. The findings reveal that the European debt crisis also caused bad impacts on the DAL of the three groups of airlines. However, the impact of the European debt crisis on their efficiency appears to vary. Table 4 also shows that the DAL of the total sample decreases by 21.021 between 2011 and 2012, and the DAL of the low group companies' DAL decreases by 36.976 between 2011 and 2012. On the other hand, the high group companies' DAL decreases by 10.299 during the same period. These results show that while airlines with fewer LEV experienced small decreases after 2007–2008 global financial crisis, their comebacks were greater than those with higher LEV, which encountered slumps in 2011 and 2012.

Subsequently, we divide $RISK$ into three categories: high scope, middle scope and low scope, as shown in Table 5. The low group consisted of those companies with a mean of $RISK$ smaller than 0.25 between 2008 and 2013. The high group consisted of those companies with a mean of $RISK$ bigger than 0.36 between 2008 and 2013. We also conduct a Kruskal–Wallis test. Panel B of Table 5 shows that, first, the low group companies' DAL is higher than the high group companies' DAL from 2008 to 2013. Second, the scores of all groups of companies increase from 2008 to 2013, except for the decline from 2011 to 2012. The DAL of the total sample in Panel A decreases by 21.021 between 2011 and 2012, and DAL of the low group companies decreases by 12.08 between 2011 and 2012. On the other hand, the high group companies' DAL decreases by 6.059. Again, the results imply that airlines with a lower level of $RISK$ were more able to return strongly after the bad consequences of the financial slump as compared to those with more $RISK$.

4.2. Asset lightness and dynamic performance

Truncated regression with a bootstrapping method should be used in DEA-application studies to explore the impacts of exogenous factors on efficiency scores, because the technique enables consistent estimators of the regression coefficients to be derived (Simar and Wilson, 2007). Following prior studies (for examples, Barros and Peypoch, 2009; Lee and Worthington, 2014), we also apply truncated regression with a bootstrapping method to assess the impact of DAL on efficiency. The regression model is stated as follows.

$$TE_{it} = \delta_1 + \beta_1 DAL_{it} + \beta_2 LEV_{it} + \beta_3 RISK_{it} + \beta_4 FSIZE_{it} + \beta_5 AGE_{it} + \beta_6 GROWTH_{it} + \varepsilon_{it}$$

where δ is the intercept, ε_{it} is the residual, and subscripts i and t indicate firm and time, respectively. TE_{it} is firm i's dynamic efficiency scores in year t. With respect to control variables, leverage (LEV_{it}) is the product of total liabilities divided by total assets; firm risk ($RISK_{it}$) is the product of long-term debt divided by total assets; firm size ($FSIZE_{it}$) is the logged value of total assets; firm age (AGE_{it}) is the number of years since the establishment of an airline; and growth opportunities ($GROWTH$) is the changes in revenues.

The empirical results in Table 6 show that the significantly positive coefficient of the independent variable, DAL ($\beta = 0.335$, $p = 0.000$) indicates that the asset-light strategy has positive impacts on the dynamic efficiency of airlines. The result is obtained after controlling for LEV, $RISK$, $FSIZE$, AGE and $GROWTH$ (Contractor et al., 2003; Kotabe et al., 2002; Sridharan, 1996), enhancing the validity of the regression test because the control variables might have the potential to reduce the effects of asset-lightness on efficiency. A noteworthy finding on the control variables is that LEV has a negative impact on dynamic efficiency (TE), while $RISK$ has a positive impact on the efficiency. A possible explanation is that the former variable measures total liabilities including short-term debt, while the latter represents only long-term debts. In other words, global airlines should consider employing long-term debts.

4.3. Discussion and managerial implications

One of the purposes of this study was to investigate whether the degree of implementation of asset-lightness impacts corporate performance. As predicted, the findings demonstrate that the degree of asset-lightness positively impacts corporate performance. This result is consistent with those of prior studies, which indicate that the adoption of the asset-light strategy is able to generate a competitive advantage and superior performance, consistent with prior studies (for examples, Liou, 2011; Tang and Liou, 2010; Wen

[3] The threshold setting is based on three equal distributions of each variable. This grouping is done also based on the idea that Federal Aviation Administration classifies airlines into Major (high scope), National (middle scope) and Regional (low scope) based on airlines' annual operating revenues. Accordingly, it is expected that major airlines have higher LEV and $RISK$ in relation to national and regional airlines.

Table 4
The relationship between *DAL* and operating characteristic: *LEV*.

Classification	*DAL*						Overall mean
	2008	2009	2010	2011	2012	2013	
Panel A: Total sample							
Mean (N = 49)	−1.794	−1.548	15.424	26.918	5.897	26.462	11.893
Panel B: By LEV							
High (N = 19)	−28.530	−16.056	11.039	−15.573	−25.872	−13.015	−14.668
Middle (N = 17)	−0.312	−9.271	18.205	38.298	17.494	35.330	16.624
Low (N = 13)	35.345	29.755	18.196	74.139	37.163	72.565	44.527
Kruskal-Wallis (N = 49)	0.002	0.086	0.412	0.003	0.001	0.000	0.000

Table 5
The relationship between DAL and operating characteristic: *RISK*.

Classification	*DAL*						Overall mean
	2008	2009	2010	2011	2012	2013	
Panel A: Total sample							
Mean (N = 49)	−1.794	−1.548	15.424	26.918	5.897	26.462	11.893
Panel B: By RISK							
High (N = 16)	−12.464	−6.343	14.119	−11.075	−17.134	−6.037	−6.489
Middle (N = 15)	−18.722	7.701	21.880	51.568	3.857	21.289	14.596
Low (N = 18)	21.797	−4.993	11.204	40.148	28.068	59.662	25.981
Kruskal-Wallis (N = 49)	0.051	0.766	0.773	0.044	0.216	0.016	0.177

Table 6
The results of truncated regression (N = 294 firm-year observations).

Variable	Coefficient	P-value
Constant	0.167	0.532
DAL	0.335	0.000
LEV	−2.610	0.000
RISK	2.314	0.000
FSIZE	0.152	0.000
AGE	−0.003	0.027
GROWTH	0.057	0.785
Adjusted R-square	0.289	

et al., 2012). As a whole, although financial reports are able to provide an impartial picture of financial position and performance, they do not reflect any light assets, which are more value-added. In other words, financial reports are unable to entirely reflect the true value of an enterprise. Light assets are resources which can generate both a competitive advantage and firm value, and as a result, they are able to reasonably predict the potential future growth of corporations. This study reveals that asset lightness can be the main corporate strategy in this challenging business world for airlines to sustain their business.

Furthermore, of the 49 sample airlines, we find that 14 of them achieved overall efficiency of unity throughout the sample period of 2008–2013. Among all, Qantas Airways is found to have a strategic objective in growing “asset-light” businesses that deliver attractive returns.[4] The average *DAL* of these efficient airlines amounted to 416.91 (about 28 percent of them are with negative values of *DAL*) as compared to the remaining 35 relatively inefficient airlines, which are with a *DAL* value of only 165.86 (about 49 percent of them are with negative values of *DAL*). In summary, this study recommends that managers in the airline industry can improve their competitive advantage based on the asset-light strategy.

5. Conclusion

Prior studies have examined the impact of the asset-light strategy on firm performance, with positive, negative, or inconclusive results being found. This study investigates the association between the degree of asset-lightness and the dynamic efficiency of global airlines. With respect to dynamic efficiency, we adopt the longitudinal view of the production process to assess the dynamic efficiency of global airlines, considering carry-overs that are carried from one term to another. As for the asset-light valuation model, we apply the approach as identified in (Liou, 2011). The DEA outcomes show that airlines were not efficient in utilizing their inputs to generate outputs, especially during financial crises. The regression results support our prediction that the degree of asset-lightness positively affects dynamic efficiency. By outsourcing, a firm is able to reduce its capital investment in a number of tangible assets and thereby increase both ROA and ROE.

As previously stated, this paper sheds new light on the airline industry and creates opportunities for further study. Future research may look into other industries, such as the semiconductor industry, that might have to significantly rely on light assets. Furthermore, future studies can also include mediating variables or advance new approaches to measuring *DAL*.

Appendix I

List of 49 sample airlines

[4] Source: http://www.asx.com.au/asxpdf/20111212/pdf/4236jzlv0gx8wc.pdf. See also page 18 in http://www.monarchholdingslimited.com/media/30309/The-Monarch-Group—Online-Annual-Report-2012.pdf for relevant words like “Flexible, asset-light model”.

No.	Airline	No.	Airline
1	AEGEAN AIRLINES	26	GOL LINHAS AEREAS INTELIGENT
2	AER LINGUS GROUP PLC	27	HAWAIIAN HOLDINGS INC
3	AEROFLOT-RUSSIAN INTL AIRL	28	ICELANDAIR GROUP HLDGS
4	AIR ARABIA PJSC	29	INTL CONSOL AIRLINES GROUP
5	AIR CHINA LTD	30	JETBLUE AIRWAYS CORP
6	AIR FRANCE - KLM	31	KENYA AIRWAYS
7	AIR MAURITIUS LTD	32	KNAFAIM HOLDINGS LTD
8	AIR NEW ZEALAND LTD	33	KOREAN AIR LINES CO LTD
9	AIRASIA BHD	34	LATAM AIRLINES GROUP SA
10	ANA HOLDINGS INC	35	NORWEGIAN AIR SHUTTLE ASA
11	ASIANA AIRLINES INC	36	PANALPINA WELTTRANSPORT AG
12	CATHAY PACIFIC AIRWAYS LTD	37	QANTAS AIRWAYS LTD
13	CHINA AIRLINES	38	REGIONAL EXPRESS HLDGS LTD
14	CHINA SOUTHERN AIRLINES	39	REPUBLIC AIRWAYS HLDGS INC
15	CHORUS AVIATION INC	40	RYANAIR HOLDINGS PLC
16	CITIC OFFSHORE HELICOPTER CO	41	SAS AB
17	COPA HOLDINGS SA	42	SINGAPORE AIRLINES LTD
18	CROATIA AIRLINES	43	SINOTRANS AIR TRANSN DEV
19	DART GROUP PLC	44	SKYWEST INC
20	DEUTSCHE LUFTHANSA AG	45	THAI AIRWAYS INTERNATIONAL
21	DIMERCO EXPRESS CORP	46	TOLL HOLDINGS LTD
22	EASYJET PLC	47	TURK HAVA YOLLARI AO
23	EL AL ISRAEL AIRLINES LTD	48	UTAIR
24	EVA AIRWAYS CORP	49	VIRGIN AUSTRALIA HLDGS LTD
25	FINNAIR OY		

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