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Efficiency analysis of major cruise lines

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HIGHLIGHTS

- This study measured the efficiency of the top three cruise lines
- Network DEA and bootstrapped-truncated regression were used
- They were efficient at the operating stage, but varied at the non-operating stage
- Cruise lines attempting high capacity expansion were relatively inefficient
- Neglected hedging policy over financial risks also contributed to the inefficiency

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ABSTRACT

Three major cruise lines account for 82% of the total market share. Their financial statements show different results between the operating incomes and net incomes over time. To examine the major causes of the differences, this study measured the efficiency of the top three cruise lines to develop a network DEA model to analyze the cruise operations at two stages, namely operating and non-operating stages. In addition, the determinants of the efficiencies were examined using a bootstrapped-truncated regression model. Overall, cruise lines were efficient at the operating stage, but varied widely in the efficiency of the non-operating stage. Cruise lines attempting high capacity expansion were relatively inefficient because of the heavy interest payments arising from the high debt-to-capital ratio. Moreover, the neglected hedging policy regarding the financial risks also contributed to the inefficiency.

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1. Introduction

Cruise tourism has witnessed substantial growth in the tourism market over the last few decades. From 1980 to 2014, the annual growth rate of cruise passengers was 7.2% (FCCA, 2015), where 22.1 million passengers enjoyed cruise travel in 2014 alone. The future of the industry is also encouraging. According to Cruise Market Watch, the number of passengers are projected to grow to 25 million in 2019 with an average growth rate of 4.5%. Although cruise tourism comprises only a fraction of the total tourism industry, whose total revenue amounted to \$ 40 billion in 2015, the per capita expenditure of cruise passengers is more than double the amount of general tourists; in 2014, each passenger paid nearly \$ 1797 to cruise lines for their service while other general tourists spent \$ 830 (UNWTO, 2015). The substantial spending of cruise passengers, together with

the high growth rates indicate that the cruise industry has great market potential. Therefore, policy makers and researchers have paid close attention to the economic impacts of cruise tourism at the national or regional level (Braun, Xander, & White, 2002; Dwyer, Douglas, Livaic, 2004; Chang, Park, Liu, & Roh, 2016b; Dwyer & Forsyth, 1998).

Cruise Market Watch reports several key statistics that characterize the cruise industry. For one thing, the industry is dominated by three major cruise lines. Carnival Corporation & plc (CCL) is the leader in the global market. In 2015, it carried 48.1% of passengers and collected 42.4% of revenue in the industry. Royal Caribbean Ltd. (RCL) and Norwegian Cruise Line (NCL) come next with the passenger and revenue share being 23.1% and 22.1%, and 10.4% and 12.4%, respectively. The oligopolistic market structure is rooted from two factors: the enormous fixed costs required in cruise line operation and the high entry barrier (Papatheodorou, 2006). First, potential entrants should purchase cruise ships to operate, which costs almost a billion dollars per ship. To recover the fixed costs, entrants need to build a substantial customer base. Second, it is not easy for new comers to establish a passenger base due to brand-

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awareness and reputation effects, meaning that cruise passengers tend to prefer well-established cruise lines to reduce their risk of travel involving high expenditure.

Provided promising market conditions and a strong entry barrier, the major cruise lines are supposed to enjoy substantial market power and collect massive profits. On the other hand, this is not always true when looking into the performance of the lines. Table 1 presents a snapshot of financial statements of the major cruise lines. All three lines have performed well in generating their revenues, but showed different outcomes in making their net incomes. Together with implementing a well-planned operation, cruise companies need to leverage their profits through appropriate financial strategies. A failure in financial strategies, e.g., hedging and capital investment, can decrease the final returns substantially even when sales and physical operation are successful. The variations in their performance in the table may have been affected by divergent business strategies in operation and financial management. Therefore, an interesting research question arises; if cruise lines are efficient in both operational and financial management, and if not, which part caused the inefficiency?

Despite the importance of assessing the performance, tourism researchers have not focused on the operational or financial performance of cruise lines. Other than cruise lines, a variety of tourism units have been analyzed in the tourism literature to determine if their operation was efficient, e.g., hotels (Barros, 2005; Hwang & Chang, 2003), resorts (Goncalves, 2013), and travel agencies (Fuentes, 2011). These studies applied a widely used method, the data envelopment analysis (DEA) proposed by Charnes, Cooper, and Rhodes (1978) (henceforth, CCR model). DEA is a programming-based method to gauge the performance of organizational units in relation to their peers. The main advantage of DEA is that it does not require a production function and can handle multiple inputs and outputs. This attractive feature has made DEA pervasive among researchers.

The DEA models used in tourism papers assumed predominantly that the inputs were converted to outputs via a single production process. On the other hand, this may misrepresent many cases including cruise line operation. For example, cruise lines initially attempt to induce as many passengers as possible to generate ticket and ancillary revenues. This process is followed by profit generation, which is related to the cruise lines' efforts to maximize the net income out of their revenue. In this case, at least two stages of the production process are involved in cruise line

operation, i.e. operational and financial. Therefore, traditional DEA models with a single process used in existing works of the tourism literature are inadequate to analyze the operational procedures. Rather, it can be modelled more properly by the network DEA, which originated from Färe and Grosskopf (1996). Network DEA models are advantageous when evaluating a multi-level production process. Yu and Lee (2009) and Hsieh and Lin (2010)'s application of a network DEA model to the hotel industry showed that the model has potential merits in evaluating the tourism units by enabling a sophisticated depiction of its operation.

In this backdrop, this paper assessed the efficiency of major cruise lines. By applying a network DEA model, this study examined the cruise lines' efficiency at two stages. The first one is the "operational" stage, where cruise lines collect ticket and other miscellaneous revenues from their labor and capital expenses. The operating income earned at this stage flows into the "non-operational" stage, where the cruise lines obtain profits. The latter stage is closely related to the financial strategy of cruise lines because profits can be increased or decreased depending on the firms hedging and investment practices.

This paper contributes to tourism literature in two ways. First, the efficiency of major cruise lines was measured in a network structure. To this end, the network data envelopment analysis (DEA) model by Tone and Tsutsui (2009) was constructed. Second, this study examined the factors that determine the efficiency of cruise lines using a bootstrapped-truncated regression model in Simar and Wilson (2007). The tourism industry is affected by macro-economic factors, such as economic crises (Papatheodorou, Rosselló, Xiao, 2010), epidemics (Cooper, 2006) and global income (Jang, Bai, Hong, & O'Leary, 2004), as well as the tourism units financial strategy (Wie, 2005). Therefore, this study examined if these factors affect the efficiency of the lines using the bootstrapped-truncated regression model.

The remainder of this paper is organized as follows. Section 2 covers the theoretical background of cruise tourism and reviews the relevant papers that performed efficiency analysis in the tourism literature along with the developments of network DEA models in the theoretical DEA literature. Section 3 illustrates the network structure of cruise line operation and its mathematical formulation and specifies the estimation model that determines the efficiency. The data source, data handling, and results are presented in Section 4, and Section 5 concludes the paper.

2. Literature review

2.1. Theoretical background

Wild and Dearing (2000) defines cruise tourism as "any maritime based tour by fare paying guests onboard a vessel whose primary purpose is the carriage of passengers." As the definition suggests, cruise tourism encompasses leisure, transportation and logistics, and maritime businesses. Owing to the applied and integrated nature of the cruise industry, theoretical development and empirical research have been scant, and in-depth research for the cruise industry is growing only in recent years. Researchers examined the cruise industry mainly from three divergent angles: cruise line operation, passenger analysis, and economic effects.

Studies on cruise line operation analyzed the nature of cruise lines and their suitable management strategy. Weaver (2005) made a deep look into the cruise operation from "McDonaldization" perspective. He argued that essential indicators of McDonaldization were observed in the cruise industry, which are efficiency, calculability, predictability, and irrationality of rationality. However, he contended that inherent risk in cruise operation, e.g., safety and weather condition, and service differentiation within a ship or

Table 1
Summary of the financial statements of major cruise lines.

Cruise line	Year	Revenue	Net income	Ratio
Carnival	2009	\$13,460,000.00	\$1,790,000.00	13%
	2010	\$14,469,000.00	\$1,978,000.00	14%
	2011	\$15,793,000.00	\$1,912,000.00	12%
	2012	\$15,382,000.00	\$1,298,000.00	8%
	2013	\$15,456,000.00	\$1,078,000.00	7%
	2014	\$15,884,000.00	\$1,236,000.00	8%
Norwegian	2009	\$1,855,204.00	\$66,952.00	4%
	2010	\$2,012,128.00	\$22,986.00	1%
	2011	\$2,219,324.00	\$126,859.00	6%
	2012	\$2,276,246.00	\$168,556.00	7%
	2013	\$2,570,294.00	\$102,886.00	4%
	2014	\$3,125,881.00	\$342,601.00	11%
Royal Caribbean	2009	\$5,889,826.00	\$152,485.00	3%
	2010	\$6,752,504.00	\$515,653.00	8%
	2011	\$7,537,263.00	\$607,421.00	8%
	2012	\$7,688,024.00	\$18,287.00	0%
	2013	\$7,959,894.00	\$473,692.00	6%
	2014	\$8,073,855.00	\$764,146.00	9%

Unit: \$ thousand.

Source: Annual reports of cruise lines

across cruise lines go against the pattern of Mcdonaldization. [Ladany and Arbel \(1991\)](#) proposed a revenue management model for cruise lines to determine the optimal number of market segments and the pricing policy. To this end, passenger demand was assumed to be linear, and the equal number of market segment was considered to simplify the model. [Ji and Mazzarella \(2007\)](#) validated two frequently used revenue management models, which are modified nested class allocation model and dynamic class allocation model. [Sun, Gauri, and Webster \(2011\)](#) applied numerous forecasting methods to identify the most suitable forecasting models for revenue management of cruise lines. Their finding suggests that revenue management forecasting for hotel industry is not necessarily applicable to the cruise industry. [Wie \(2005\)](#) derived the optimal capacity investment of cruise lines when they provide homogeneous service in an oligopolistic market.

Researchers also analyzed cruise passengers, identifying their psychological and spending patterns. [Li and Petrick \(2008\)](#) paid in-depth attention to passengers' loyalty. Checking the relationship between major loyalty constructs, the authors found that cognitive, affective, and conative loyalties are sufficient to explain behavioral loyalty. The question of "why people cruise" was addressed by [Hung and Petrick \(2011\)](#). They showed that cruise motivation could be categorized into four dimensions, which are self-esteem/social recognition, escape/relaxation, learning/discovery/thrill, and bonding. [Hyun and Han \(2013\)](#) studied the effect of "other passengers' perception" on a passenger's social value, brand attachment, and willingness to pay a price premium. Their results suggest that the significant effect of other passengers' perception influence social value, and brand attachment. In addition, a mediating relationship of brand attachment on willingness to pay a price premium was identified. [Chang, Liu, Park, and Roh \(2016a\)](#) examined the determinants of cruise passengers' satisfaction. After surveying passengers before and after their trips, they inferred that satisfaction and revisit-intention were mainly explained by cruise travelers' experience on site rather than the gap between expectation and real experience.

Another popular topic among cruise researchers is economic impact analysis, which is to measure or conceptualize the direct or indirect effects of cruise industry on national or regional economy. [Dwyer and Forsyth \(1998\)](#) and [Dwyer, Douglas, and Livaic \(2004\)](#) developed a detailed conceptual framework that covers a variety of passenger expenditure types and their positive economic effects in regional and national level. [Braun et al. \(2002\)](#) used a regional input-output analysis to measure the economic impacts of cruise travels at Port Canaveral, based on the survey data of the spending of cruise lines, passengers and crews. A similar method was used by [Chang et al. \(2016b\)](#) who estimated the economic impacts at the Port of Incheon. Notable contribution of the cruise industry was observed in terms of production, labor and value-added induced effects.

2.2. Efficiency analysis

Several authors have contributed to measuring the efficiency in the tourism sector, predominantly using DEA. [Hwang and Chang \(2003\)](#) used the CCR model and Malmquist Productivity Index to analyze the performance of Taiwanese hotels. They measured the change in the managerial efficiency of the hotels over time and found a link between efficiency and strategy formulation. [Barros \(2005\)](#) evaluated the performance of Portuguese hotels using the input-oriented CCR model. He showed that the economies of scale and location were major factors that determined the hotel efficiency. The same model was used in [Köksal and Aksu \(2007\)](#), who assessed the A-Group travel agencies in Turkey. They found an insignificant difference in efficiency between the agencies

operating independently and the ones operating under a chain brand. [Barros, Botti, Peypoch, Robinot, and Solonandrasana \(2011\)](#) identified the key determinants of efficiency in French tourist destinations. Initially, they ran an output-oriented CCR model to measure the efficiency, which was followed by the bootstrapped-truncated regression of the tourist attraction features on the efficiency. Their results suggested that beach endowments, the presence of theme parks, monuments, museums, ski resorts, and natural parks improved efficiency. In their analysis of Italian tourist regions, [Bosetti, Cassinelli, and Lanza \(2007\)](#) calculated the Malmquist Productivity Index to gauge the technological and efficiency change of the regions over time. They incorporated the variables related to the environment as well as tourism service provision, claiming that the tourism regions should minimize their environmental effects to maintain competitiveness.

[Wöber and Fesenmaier \(2004\)](#) applied both input and output-oriented DEA models to evaluate the state tourism advertising programs in the U.S. By applying super efficiency, they further differentiated the rankings among the efficient programs. [Reynolds and Thompson \(2007\)](#) used the output-oriented CCR model to assess full-service restaurants in the U.S. Their approach is unconventional in that they analyzed the effects of the marginal input usage on the restaurant efficiency. To this end, they first identified a set of inputs that correlated with the outputs and treated all inputs as uncontrollable. By increasing the input usage one at a time, they found what inputs drove the efficiency improvement mostly. [Giménez-García, Martínez-Parra, and Buffa \(2007\)](#) utilized both input- and output-oriented BCC models (variable return-to-scale model) to evaluate the restaurant establishments of a Spanish fast-food chain. [Goncalves \(2013\)](#) measured the Luenberger Productivity Indicator of French ski resorts, which enabled them to examine both the technical efficiency change and technological change in the places.

All the aforementioned studies used "all-in-one" DEA models, which assumed that tourism service is provided over a single process. On the other hand, tourism service is often offered in multi-level process, e.g., tourism units may attract a number of tourists first, and then they would attempt to leverage revenue from tourists. In contrast to the tourism literature, theoretical DEA literature shows advanced model developments to represent the multi-level processes, so called "network DEA." [Färe and Grosskopf \(1996, 2000\)](#) paved the way of network DEA via introducing "intermediate outputs" to a conventional DEA model. Several applications confirmed earlier work. [Liang, Yang, Cook, and Zhu \(2006\)](#) proposed a supply-chain model, where a supplier and retailer cooperate with each other in a leader-follower relationship. [Bogetoft, Färe, Grosskopf, Hayes, and Taylor \(2009\)](#) examined the optimal investment path of firms in a manner that utilized capital and leveraged the final output production. [Tone and Tsutsui \(2009, 2014\)](#) modified the previous models, incorporating "slacks" in an efficiency measure. The primary merit of their model is that the inputs or outputs do not necessarily need to be improved equi-proportionally, and the worst aspects of firm operation are emphasized. [Chang, Park, Zou, and Kafle \(2016c\)](#) examined the financing reform of the U.S. airports in a dynamic network framework. In particular, substitutability between the passenger facility charge and airport improvement funds, which are the two major financing sources of the U.S. airports, were analyzed.

Two studies in tourism applied the network DEA. [Yu and Lee \(2009\)](#) utilized a hyperbolic network DEA model to gauge the performance of international tourist hotels. Their two stage model comprises the following: 1) the production process, where room and food service capacity are generated from labor and capital resources, and 2) the marketing process, where capacities are converted to revenues. [Hsieh and Lin \(2010\)](#) also examined

Fig. 1. Network structure of cruise line operations.

international tourist hotels with a similar network formulation to Yu and Lee, but using a different model called a relational network model.

The literature survey showed that there are significant gaps in the tourism literature. First, researchers have not examined the efficiency of cruise lines. Second, out of the many applications of DEA to tourism analysis, only two studies used network DEA models. Finally, even fewer studies, e.g., Barros et al. (2011), examined what factors influenced the efficiency. This paper contributes to the literature by filling these gaps.

3. Methodology

This section illustrates the cruise operational process of this study, and then explains its mathematical formulation and estimation model to identify the efficiency determinants.

3.1. Network structure

Fig. 1 presents the two-step operational process of cruise lines. The present research team checked the major items of the cruise companies financial statements carefully in detail for the consideration of selecting input, intermediate and output variables at the two stages. The first stage, “operating process”, refers to the revenue-generating activities of the firms. In particular, payroll, operating, and administrative expenses, and depreciation turned out to be the major input variables in producing the outputs, such as ticket and onboard revenues and operating income. The payroll and related expenses are the payments for shipboard personnel, officers, deck and engine crew, and hotel and administrative employees. The payroll was separated from overall operating expenses to reflect the degree of customer service on board ship, e.g., more payroll implies the employment of more crewmembers, which improves the service quality (Teye & Leclerc, 1998). Administrative expenses contain marketing, sales, and administration activity expenses, which are generated mainly via the shore side operation. Depreciation is allocated generally over the 30-year economic life span of the asset. The other operating expenses include the cost of passenger bookings, transportation expenses, commissions of

travel agents, fees, taxes, and other charges. Ticket revenues comprise the sales of passenger tickets, and the air transportation to or from ships. A ticket price generally includes meals, accommodation, onboard entertainment, and some non-alcoholic beverages. Onboard revenues are the sales of goods and service onboard ships, which are not included in the ticket price.

¹The next stage, non-operating process, describes the performance of cruise lines in generating profits out of the earned income. Note that the operating income serves as an intermediate output, meaning that it mediates the first and second stages. The operating income is calculated by subtracting all expenses from the total revenue. The non-operating expense is also added to the second stage, which includes the net of interest expenses and other expenses. The result of the second stage operation is the net income. This refers to the remaining portion of the total revenue after excluding the total cruise operating expenses, total other operating expenses, total non-operating expenses, and income tax expenses.

The rationale behind the network structure is that it closely follows the line of financial statements available from cruise lines. That is, by describing the network in parallel with the accounting procedures, the cruise lines’ performance can be determined from the financial statements in broadly two parts: the operational and non-operational efficiencies. The former is closely associated with the firms sales activities while the latter with financial strategies, such as hedging, taxation, and investment.

3.2. Efficiency measurement model

The slacks-based network DEA model in Tone and Tsutsui (2009) was used to measure the efficiency of cruise lines. As reported by Tone (2001), an efficiency measure focusing primarily on slacks has merits in that it allows firms to improve the inputs or outputs in an asymmetric proportion, where other DEA models assume an equiproportional increase in the outputs or reduction of inputs. This is effective because the firms most inefficient part of the operation can be revealed easily based on more realistic assumptions.

As illustrated in Fig. 1, the cruise lines operation can be split into two stages. $k = 1, 2$ is an index that indicates the operational and non-operational stages, respectively. At a specific stage, k , individual cruise line o uses a combination of inputs $\mathbf{x}_o^k = (x_{1o}^k, x_{2o}^k, \dots, x_{io}^k)$ to produce the network outputs $\mathbf{y}_o^k = (y_{1o}^k, y_{2o}^k, \dots, y_{ro}^k)$. Both stages are connected through intermediate outputs $\mathbf{z}_o = (z_{1o}, z_{2o}, \dots, z_{wo})$, which serve as outputs for stage 1 and as inputs for stage 2. The efficiency of a cruise line can be measured using the following linear program:

¹ Note that the second stage is not a simple ratio analysis of output to input. Firstly, the second stage involves more than one input since the intermediate output (operating income) resulting from the first stage serves as input at the next stage. Next, the second stage is based on ‘peer evaluation’, so the resulting efficiency score is interpreted as the extent to which an evaluated firm can improve its input or output compared to the best performers. On the other hand, output/input ratio denotes how much firms can produce per given input.

$$\text{minimize } \rho^o = \frac{1 - \sum_{k=1}^K \sum_{i=1}^{m_k} \frac{w_k^k s_i^{k-}}{m_k x_{io}^k}}{1 + \sum_{k=1}^K \sum_{r=1}^{r_k} \frac{w_k^k s_r^{k+}}{r_k y_{ro}^k}}$$

subject to

$$\sum_{j=1}^n \lambda_j^k x_{ij}^k = x_{io}^k - s_i^{k-}, \quad i \in I_k, \quad \forall k, \quad (1)$$

$$\sum_{j=1}^n \lambda_j^k y_{rj}^k = y_{ro}^k + s_r^{k+}, \quad r \in R_k, \quad \forall k, \quad (2)$$

$$\sum_{j=1}^n \lambda_j^1 z_{wjo} = \sum_{j=1}^n \lambda_j^2 z_{wjo}, \quad w \in W, \quad (3)$$

$$\sum_{j=1}^n \lambda_j^k = 1, \quad \forall k, \quad (4)$$

$$\lambda_j^k \geq 0, \quad \forall k, j,$$

$$s_i^{k-} \geq 0, \quad \forall k, i,$$

$$s_r^{k+} \geq 0, \quad \forall k, r,$$

where λ_j^k is a weight that indicates how much a cruise line o benchmarks another cruise line j . I_k , R_k , and W are the set of inputs, outputs and intermediate outputs at stage k , respectively. w^k represents the importance of stage k ($w^1 + w^2 = 1$), m_k is the number of inputs, r_k is the number of outputs, and $\rho^o \in [0, 1]$ the efficiency score of cruise line o . The objective function fully identifies the slacks of inputs and outputs in the numerator and denominator, respectively. The nonlinear objective function should be solved by the fractional programming method, whose detailed procedure is explained by Tone (2001); Tone, Tsutsui, (2009). Among the constraints, (1) expresses that cruise line o can reduce its input level by s_i^{k-} compared to the best practice level $\sum_{j=1}^n \lambda_j^k x_{ij}^k$. Similarly, (2) shows that the cruise line o has potential to increase output by s_r^{k+} . Constraint (3) is a newly incorporated component into the network DEA, which states that the intermediate output produced at the first stage directly flows to the second stage. In other words, the intermediate outputs are not added or lost when they are moved through the stages. Eq. (4) imposes the variable returns-to-scale assumption of the cruise line operation.

After obtaining the solution values from the above model, efficiency scores are calculated as,

$$\rho_k^{o*} = \frac{1 - \sum_{i=1}^{m_k} \frac{s_i^{k-}}{m_k x_{io}^k}}{1 + \sum_{r=1}^{r_k} \frac{s_r^{k+}}{r_k y_{ro}^k}} : \text{efficiency of stage } k, \quad (5)$$

$$\rho^{o*} = \frac{1 - \sum_{k=1}^K \sum_{i=1}^{m_k} \frac{w_k^k s_i^{k-}}{m_k x_{io}^k}}{1 + \sum_{k=1}^K \sum_{r=1}^{r_k} \frac{w_k^k s_r^{k+}}{r_k y_{ro}^k}} : \text{overall efficiency.} \quad (6)$$

Asterisk in (5) and (6) denotes the optimal solution of the efficiency measurement model. The Efficiency of stage k (ρ_k^{o*}) in (5) only contains the corresponding term at stage k , whereas overall efficiency (ρ^{o*}) in (6) incorporates all the inputs and output slacks at both stages. Thus, (6) can be considered as the averaged operating and non-operating performance of a specific cruise line.

3.3. Bootstrapped truncated regression

To find the determining factors on cruise efficiency, a regression model is used. Numerous existent papers (Barros, 2004; Chang et al., 2016c; Gillen & Lall, 1997; Zou, Kafle, Chang, & Park, 2015) applied Tobit regression for this purpose, which assumes a censored normal distribution, for efficiency scores are one at best. Simar and Wilson (2007), however, argued that the application of Tobit regression is erroneous because it ignores the data generating process (DGP) of observed variables. Specifically, “environmental variables (or contextual variables)” affect firms inherent efficiency, which in turn are realized as input and output levels. This can be mathematically expressed as,

$$f(\mathbf{x}_i, \boldsymbol{\eta}_i, \delta_i, \mathbf{z}_i) = f(\mathbf{x}_i, \boldsymbol{\eta}_i | \delta_i, \mathbf{z}_i) f(\delta_i, \mathbf{z}_i) f(\mathbf{z}_i), \quad (7)$$

where $f(\cdot)$ is the probability density function of drawing observations, $\mathbf{x}_i$ is the vector of observed inputs, $\boldsymbol{\eta}_i$ the reparametrized output vector, δ_i the true unknown efficiency, $\mathbf{z}_i$ the matrix of determinants that affect firms' performance. Subscript i denotes a specific firm. Note that the right-hand side represents the logical sequence of the DGP: the probability of inspecting observed inputs and outputs is conditioned on efficiency and environmental variables, with the latter being the ultimate precursor. DEA measurement, however, follows the sequence of the DGP inversely: observed inputs and outputs are used to calculate efficiency, and the effects of environmental variables on the efficiency are estimated by regression. To see this, let the true model of efficiency-determinants relationship specified as $\delta_i = \mathbf{z}_i \boldsymbol{\beta} + \varepsilon_i$, where $\boldsymbol{\beta}$ is the vector of marginal determinant effects and ε_i an error term. If DEA efficiency score is used with Tobit regression, it leads to

$$\begin{aligned} \delta_i &= \hat{\delta}_i - \text{Bias}(\hat{\delta}_i) - u_i = \mathbf{z}_i \boldsymbol{\beta} + \varepsilon_i \rightarrow \hat{\delta}_i \\ &= \mathbf{z}_i \boldsymbol{\beta} + \varepsilon_i + \text{Bias}(\hat{\delta}_i) + u_i. \end{aligned} \quad (8)$$

$\text{Bias}(\hat{\delta}_i) = E(\hat{\delta}_i) - \delta_i$ is the difference between the calculated efficiency $\hat{\delta}_i$ and the unknown true efficiency δ_i . $\text{Bias}(\hat{\delta}_i)$ can be regarded as a noise stemming from DGP. u_i is an additional error term. Eq. (8) suggests that Tobit regression abandons $\text{Bias}(\hat{\delta}_i) + u_i$ terms, which may vanish asymptotically but produces inefficient and less reliable estimates.

To cope with this shortfall, Simar and Wilson (2007) proposed a bootstrapped-truncated regression to improve reliability of estimates. The merit of this technique was acknowledged in many studies (Barros et al., 2011; Wanke, Azad, & Barros, 2016; Wanke, Barros, Emrouznejad, 2016). We used the STATA program and a user-contributed package ‘simarwilson’ (Tauchmann, 2016).

3.4. Environmental variables in bootstrapped-truncated regression

The estimation model is specified as follows:

$$\text{Efficiency}_i = \beta_0 + \sum_n \delta_n X_{n,i} + \varepsilon_i, \quad (9)$$

Subscript i indicates a specific cruise line. Efficiency_i is the efficiency scores calculated using the efficiency measurement model. Two types of efficiency were assessed as dependent variables, which are the stage-specific and overall efficiencies, i.e. ρ_k^{o*} and ρ^{o*} in (5) and (6). β_0 and δ_n are the coefficients to be estimated and $X_{n,i}$ is a set of independent variables. ε_i is an error term.

We selected explanatory variables based on the literature. First, empirical evidence suggests that the tourism industry is affected by macro-economic factors, especially economic crises. Subprime

mortgage crisis in 2008, for example, put a great dent on the tourism industry. Papatheodorou, Rosselló, and Xiao (2010) provided impressive summary of the economic shock in 2008 that had over the overall tourism industry and drew its implications. Smeral (2010)'s times-series analysis showed that tourism imports would decline substantially due to the economic recession. Song and Lin (2010)'s finding also agrees with Smeral (2010), but the former added that long-haul transit market was particularly susceptible to loss.

Moreover, the outbreak of epidemics can be influential to the tourism industry. Baxter and Bowen (2004) analyzed how foot-and-mouth disease (FMD) in the United Kingdom (1967–1968 and 2001) affected tourism. They noted that the timing, location, prevalence, media coverage could intensify or relieve the severity of FMD on the tourism industry. Cooper (2006) examined the impact of Severe Acute Respiratory Syndrome (SARS) outbreak on Japanese tourism market. Both inbound and outbound travels in Japan decreased substantially due to tourists avoidance to “SARS infected areas”.

Other factors, such as consumer income and financial strategy of tourism unit, can be crucial in the viability of tourism industry. De La Viña and Ford (2001)'s survey results suggested that high-income consumers were more willing to enjoy cruise travel. In a similar vein, Jang et al. (2004) studied the spending patterns of Japanese travelers in the U.S. market. Their survey results stated that high-income people spent more than other groups in general.

Financial strategy appears to be decisive for cruise lines' profitability because they require huge initial investment in their capacity (Wie, 2005). Nevertheless, the relationship between financial strategy and tourism units' financial performance received little attention from tourism researchers. Some authors in the other field of study, however, found significant relationship between financial orientation and performance. Exploring the airline industry's response to September 11 attack, Pires and Fernandes, (2012) evidenced that airlines with lower leverage showed greater financial productivity growth after the incident. In a study of banking performance, Beck, Demirgüç-Kunt, and Merrouche (2013) presented that banks holding high equity-capital ratio maintained greater financial performance during the subprime mortgage crisis.

On top of this inspection, the following variables were included: *Economic shock*, *Epidemic*, *Other accidents*, *Purchasing-Power-Parity (PPP)*, *Total debt to capital and payroll*. *Economic shock* is the indicator variable that takes value ‘1’ for observations in year 2004, 2012, and 2013 while having value ‘0’ for other observations. These are periods when the cruise lines could have been affected by economic crises, e.g., oil shock in 2004; subprime mortgage shock in 2009; recession in Spain and Italy in 2012; and Euro zone crisis in 2013. Likewise, *Epidemic* is the indicator variable where value ‘1’ is assigned for observations in 2003 and 2009 and ‘0’ for the rest of observations. This is to represent the negative impacts of epidemic disease, e.g., SARS in 2003 and Mexico flu in 2009. The last indicator variable is *Other accidents*, where ‘1’ is encoded for years 2001, 2003, and 2012. Disastrous accidents happened in these periods: September 11 attack in 2001; the breakout of Iraq War in 2003; and the capsizing of Costa Concordia (2012). *PPP* is the valuation of GDP in 37 advanced countries scaled by their purchasing power. *Total debt to capital* is the ratio of total debts to capital in financial statements, where the total debt is the sum of both short-term and long-term debts, and the capital indicates the aggregate value of the total debt and shareholder equity. An additional variable, *Payroll*, which is total expenses on wages, is included to control the effects of cruise lines' size.

4. Data and results

4.1. Data

Detailed financial information of the three major cruise lines was collected from their annual reports. The CCL data were collected from 2002 to 2014, the RCL data were from 1997 to 2014, and NCL data were from 2003 to 2014. All 44 observations were pooled into the analysis (Asmild, Paradi, Aggarwall, & Schaffnit, 2004; Ha, Wan, Yoshida, & Zhang, 2013; Merkert & Hensher, 2011). All monetary values were standardized to the value in 2009 using the GDP deflator. In particular, the GDP growth rate of 37 advanced countries, e.g., Greece, Italy, and the U.S., was used as most cruise routes have been centered on these countries. Table 2 lists the descriptive statistics of the variables used in the efficiency measurement. Note that some values in “operating income” and “net income” variables are negative. Because DEA is incapable of working with negative data, an appropriate method was necessary to handle them. The next subsection will discuss our choice of the method based on the review of previous approaches.

Furthermore, performing DEA requires the minimum number of sample size. Let N be the number of outputs, M is the number of inputs, and K is the number of observations. The following condition should be satisfied (Husain, Abdullah, & Kuman, 2000):

$$K \geq 3(N + M)$$

In the case of our data, $N = 4$ (including an intermediate output), $M = 5$ and $K = 43$. Therefore, the above condition holds.

Moreover, the data set used in DEA should satisfy the isotonicity (Charnes, Cooper, Golany, Seiford, & Stutz, 1985), i.e., the use of more inputs leads to higher output production to obtain meaningful results. To check isotonicity, a correlation matrix among the input and output variables was constructed, as listed in Table 3. All coefficients are significantly positive at either 1% or 5% level, suggesting that the data meet the isotonicity fairly well.

4.2. Handling negative data

DEA researchers proposed divergent ways to solve negative data problem. Pastor (1996) discussed how to massage negative variables in translation-invariant DEA models e.g., additive model. For such models, he showed that the data can be handled by adding an arbitrarily large fixed value to observations in potentially negative variables. Seiford and Zhu (1999, 1996) chose rather extreme approach: they removed the observations that contain negative values from their samples. More recently, Portela, Thanassoulis, and Simpson (2004) developed a “range directional distance function” model, which is to construct an artificially constructed frontier by setting improvement vector at $(\mathbf{x} - \min(\mathbf{x}), \max(\mathbf{y}) - \mathbf{y})$. This method was extended by Sharp, Meng, and Liu (2007), who proposed a slack-based measure (SBM) of the previous model. Tone (2001) suggested a simple approach by replacing negative values with minimum positive ones.

Most of the above methods, however, seems inapplicable in this paper. Since the network SBM model is not translation-invariant, Pastor (1996)'s solution does not apply in our case. Removing observations with negative value is problematic because a substantial number of sample would be lost, which would produce biased efficiency scores. Portela et al. (2004) and Sharp et al. (2007) seem to be the reasonable approach to be employed for our data. Nevertheless, their models are invalid for the network DEA model because they do not provide clear guidelines when negative values arise in intermediate output variables, which serves as output at the preceding stage and input at the subsequent stage. In other

Table 2
Summary statistics of variables.

Variable	Min.	Med.	Mean.	Max.
<i>Stage 1 output</i>				
Passenger ticket revenue	3346	1,563,363	1,964,489	5,893,847
Onboard and other revenue	898	604,755	741,984.9	2,237,176
<i>Stage 1 input</i>				
Payroll and related	458	290,822	316,361.9	847,641
Total cruise operating expenses	1872	1,185,374	1,460,812	4,463,533
Marketing, selling and administrative	609	299,827	395,098.5	1,251,013
Depreciation and amortization	382	170,191	234,029.6	772,445
<i>Intermediate output</i>				
Operating income	−63247	303,555	956,352.3	7,959,894
<i>Stage 2 output</i>				
Net income	−226,962	66,952	186,589.2	764,146
<i>Stage 2 input</i>				
Non-operating expenses	83	157,965	142,628	384,823

Unit: \$ thousand.

Table 3
Correlation between the inputs and outputs.

Output Input	Passenger ticket revenue	Onboard and other revenue	Operating income (\$)	Net income (\$)
Payroll and related	0.9712*** ^{a,b}	0.9736***	0.6748***	0.8015***
Total cruise operating expenses	0.9967***	0.9979***	0.6753***	0.3629**
Marketing, selling and administrative	0.811***	0.8046***	0.5285***	0.8046***
Depreciation and amortization	0.9907***	0.9904***	0.7142***	0.7653***
Non-operating expenses	0.8798***	0.8875***	0.5552***	0.6072***

^a Results for correlation test with $H_0: \rho = 0$ and $N = 43$ are reported.

^b *: $p < 0.05$, ***: $p < 0.01$.

words, if negative values occur in intermediate output, it is unclear whether to scale them with maximum or minimum values.

At this stage, it seems that Tone (2001)'s suggestion is suitable for our analysis. He recommends transforming negative output values by

$$y_o \leftarrow \frac{1}{10} \min \{y_j | y_j > 0, j = 1, \dots, n\}$$

where, y_j is an output observation of firm j . This way, bad performers are severely penalized. Even though accuracy is lost to some extent, this treatment is simple and clear, and more importantly, we could not find any better feasible alternative than this.

One can argue that this approach still has a problem of bias. In this aspect, we find that no literature is available to address this issue. Therefore, we have developed our new approach to assess the potential measurement errors that might be inherent in this approximation indirectly through data translation. First, we added a sufficiently large positive constant α to a variable with negative observations, i.e. $Y_o = y_o + \alpha > 0$. Next, we calculated the second stage efficiency score with translated data (because negative values were present in the second stage output, so affecting the second stage efficiency more severely). Let the scores be $\rho_{translation}^o$ and the unknown true efficiency be ρ_{true}^o . These scores have the relationship $\rho_{translation}^o > \rho_{true}^o$. Subtracting the efficiency score calculated through Tone's suggestion, ρ_{Tone}^o , on both sides, we have

$$\rho_{translation}^o - \rho_{Tone}^o > \rho_{true}^o - \rho_{Tone}^o$$

The right-hand side is the measurement error. If $\rho_{translation}^o - \rho_{Tone}^o$ and ρ_{Tone}^o are close to zero, the measurement error would be negligible. Our calculation shows that the average of $\rho_{translation}^o - \rho_{Tone}^o$ and ρ_{Tone}^o for negative observations are 0.04 and 0.001 respectively. This is small enough to be negligible considering the range of efficiency scores [0,1]. Thus, we conclude the

measurement error would not be significant for our data.

4.3. Results and discussion

Table 4 lists the efficiency scores of the cruise lines. The year of observation, and its corresponding efficiencies are reported. Fig. 2 summarizes the average efficiency to gain greater insight. A quick inspection reveals that CCL is most efficient in terms of the overall efficiency with average 0.883, followed in order by RCL with 0.695 and NCL with 0.275. Regarding the changes in efficiency over time, there appears to be no clear pattern because the efficiency scores fluctuate widely.

The operating efficiency (stage 1) is similar among cruise lines, as shown in Fig. 2, and all of them performed relatively well from an operational perspective. The non-operating efficiency, however, showed a completely different picture: the difference in average efficiency between the best performer (CCL) and the poorest one (NCL) is 0.623 (=0.821–0.193). The RCL is in between with the average efficiency of 0.695. These results suggest that the variation of the cruise line performance arises mainly at the non-operating stage, which reflects the companies financial or accounting activities, e.g., interest payment and taxation. The efficiency scores suggest that relatively inefficient RCL and NCL can increase their net income (the final output of the non-operating stage) by improving their financial strategies. On the other hand, to identify the possible financial strategies to leverage their income, the determinants of efficiency should be examined.

Table 5 lists the results that regressed the efficiency on several possible determinants. Model 1 has the overall efficiency as the dependent variable, Model 2 has the operating efficiency, and Model 3 has the non-operating efficiency. To check the multicollinearity among independent variables, variance inflation factors (VIF) are reported in the last column. VIF values of *Total debt to capital* and *payroll* are higher than the generally accepted cutoff 5 (Craney &

Table 4
Efficiency of major cruise lines.

Year	Overall eff.	Operating stage eff.	Non-operating stage eff.
<i>Carnival</i>			
2002	1.000	1.000	1.000
2003	0.874	0.942	0.807
2004	0.878	0.975	0.800
2005	0.918	1.000	0.849
2006	0.961	1.000	0.925
2007	0.987	0.974	1.000
2008	0.925	1.000	0.860
2009	0.823	0.932	0.742
2010	0.867	1.000	0.749
2011	0.903	1.000	0.810
2012	0.771	0.908	0.678
2013	1.000	1.000	1.000
2014	0.577	0.858	0.451
Average	0.883	0.968	0.821
<i>Royal Caribbean</i>			
1997	0.564	0.984	0.342
1998	0.657	1.000	0.414
1999	0.832	1.000	0.707
2000	0.782	1.000	0.624
2001	0.508	0.926	0.314
2002	0.651	1.000	0.389
2003	0.508	0.921	0.296
2004	0.626	0.982	0.373
2005	1.000	1.000	1.000
2006	0.767	1.000	0.574
2007	0.721	1.000	0.475
2008	0.758	1.000	0.541
2009	0.351	0.883	0.168
2010	0.727	0.958	0.538
2011	1.000	1.000	1.000
2012	0.065	0.976	0.022
2013	1.000	1.000	1.000
2014	1.000	1.000	1.000
Average	0.695	0.979	0.543
<i>Norwegian</i>			
2003	0.001	0.864	0.001
2004	0.003	0.961	0.002
2005	1.000	1.000	1.000 ^a
2006	0.012	1.000	0.005
2007	0.001	0.960	0.000
2008	0.001	0.836	0.000
2009	0.340	0.866	0.223
2010	0.093	0.890	0.046
2011	0.385	0.992	0.201
2012	0.549	1.000	0.243
2013	0.269	0.968	0.123
2014	0.645	0.921	0.473
Average	0.275	0.938	0.193

^a The abnormal jump in efficiency could be due to adding three new cruise ships into service and “improved pricing environment”, according to the annual report of NCL. As a result, positive net income was observed in 2005, whereas negative net income was experienced in the preceding and subsequent few years.

Fig. 2. Average efficiency of cruise lines.

Surles, 2002), meaning that multicollinearity may exist for these variables. This, however, does not seem problematic because *Total debt to capital* is significant even in the face of high VIF or large variance (see O'Brien (2007)) and *payroll* is not the variable of interest (see Allison (2012)). In addition, Wald statistics are presented in the bottom row to assess generic model fit, and all of them were significant, so every model was deemed to be meaningful.

The estimates of Model 1 suggest that the *Total debt to capital* and *Economic crisis* had a significant impact on the *overall efficiency*. More attention is paid to Models 2 and 3 for a deeper investigation because the overall efficiency is captured as an averaged effect between the operating and non-operating efficiency.

In Model 2, *Epidemic* and *Economic crisis* show significant relationships with the operating efficiency. As for *Epidemic*, note that two major events were included in the epidemic dummy variables, which exerted substantial damage to cruise travel. The first was the SARS outbreak in 2003; there were more than 3500 patients, of whom more than 2800 patients lived in China and Hong Kong. The infectious nature of the disease deterred cruise travel as people avoided the heavily crowded area. Second, an outbreak of Mexico Flu in mid-North America in 2009 also struck the cruise industry. The region had the largest cruise market in the world, so cruise lines must have suffered from a tremendous reduction in travel by the flu. This result is in line with existing empirical evidence (Baxter & Bowen, 2004; Cooper, 2006), which concludes negative impacts of epidemics on the tourism industry.

The sign of *Economic crisis* is unintuitive. The data suggested that ticket and miscellaneous revenue declined during economic recession. However, this does not mean that their efficiency also fell. Cruise lines undertook major restructuring swiftly and rigorously, which reduced operating costs greatly. For example, NCL cut its payroll expenses from \$377 to \$252 million (33.1%) and the remaining operating cost after excluding the payroll expenses from \$1.2 to 1.0 billion (16.7%) between 2008 and 2009, whereas revenue decreased from \$2.1 to \$1.86 billion (9.7%) in the same period. A similar pattern was observed for other cruise lines as well, which helped to increase their efficiency in grim days. This is new insight that was not highlighted in the past research (Papatheodorou et al., 2010; Song & Lin, 2010), which only focused on the indicators such as the number of tourists.

Purchasing power parity is not a significant indicator of all efficiency types, which is in contrast with other empirical evidences (De La Viña & Ford, 2001; Jang et al., 2004). *Other accidents* and *Payroll* are not significant either. This indicates that cruise travelers are relatively insensitive to ship accident news, and the size of cruise line itself does not determine the efficiency of cruise lines.

Model 3 shows that *Total debt to capital* and *Economic crisis* affected the non-operating efficiency significantly. That is, a higher proportion of debts on capital and economic downturn deteriorated the financial performance of creating net incomes. It is interesting to see that the sign of *Economic crisis* is negative for non-operating efficiency, which is contrary to the case of operating efficiency. This implies that cruise lines financial activities, such as investment and capital utilization, are vulnerable to the economic shock, and even rigorous restructuring does not make up for the weakness.

The negative sign of *Total debt to capital* implies that higher debt-to-capital ratio affected non-operating (or financial) efficiency adversely. This is consistent with previous studies that examined financial efficiency (Pires and Fernandes, 2012; Beck et al., 2013). Fig. 3 shows the average debt to capital ratio. The figure implies intuitively that the major cruise lines have adopted an aggressive strategy in their capacity expansion by increasing debt. This tendency is more apparent in RCL and NCL, whose debt-to-capital ratio is close to double the amount of CCL's. This must have caused RCL

Table 5
Bootstrapped-truncated regression results.

Dependent variable	Model 1 Overall efficiency	Model 2 Operating efficiency	Model 3 Non-operating efficiency	VIF
Purchasing power parity (PPP)	1.21E-06 ^a (9.77E-06)	−1.63E-06 (2.63E-06)	−4.49E-07 (5.39E-06)	2.63
Total debt to capital	−3.705*** ^b (0.832)	−0.169 (0.172)	−2.534*** (0.512)	5.10
Epidemic	−0.096 (0.122)	−0.084*** (0.029)	−0.046 (0.07)	1.23
Economic crisis	−0.186* (0.105)	0.058** (0.023)	−0.133** (0.061)	1.28
Other accidents	0.05 (0.147)	0.039 (0.051)	0.025 (0.072)	1.21
Payroll	−3.13E-07 (2.62E-07)	−8.03E-08 (6.39E-08)	−1.81E-07 (1.37E-07)	6.22
Constant	2.644*** (0.462)	1.097*** (0.126)	1.823*** (0.276)	
Wald statistic	62.755***	13.322**	148.491***	
Observations	41	41	41	

^a Note: Standard errors in parentheses.

^b ***p < 0.01, **p < 0.05, *p < 0.10.

and NCL to pay more debt expenses than CCL. Accordingly, it can be inferred that the debt payments increased the burden to the lines compared to the increasing revenues arising from more ship purchases, which are financed by debt.

Another interesting point is that RCL and NCL exhibited notably different scores at the non-operating stage (RCL: 0.543, NCL: 0.193), even though debt-to-capital ratio between them differed by only 10%. This could have been attributed to their hedging policy. RCL and CCL actively hedged against fuel costs, interest rates, and exchange rates while NCL failed to do so (This was officially stated in the annual report of NCL in 2006). The failure intensified NCL's already massive debt when the interest rate escalated. Indeed, in December 31, 2006, NCL had \$2.6 billion of total debt, of which \$154.6 million was the portion of long-term borrowings, which were mostly incurred to finance ship construction. In the same year, the LIBOR and EURIBOR rate increased by 1%, increasing their burdens of debt payment. For this reason, NCL recorded huge foreign currency translation losses, e.g., total losses of \$ 25.3 million throughout 2002–2006. In addition, NCL had to bear substantial impairment losses occurring in 2008 due to the cancellation of a shipbuilding contract. Overall, NCL's neglecting the hedging strategies and the sudden cancellation of a shipbuilding contract largely contributed to the negative net income of NCL for 2003–2008. This explains NCL's exceptionally low non-operating efficiency score compared to RCL.

Linking the result to Table 1, we can infer why some cruise lines collect more net income out of their revenue. Aggressive capacity expansion strategy, i.e. purchasing and operating more ships, caused substantial debt pressure and low profitability for less-earning cruise lines (RCL and NCL). In particular, the debt burdens were felt more severely for NCL that did not prepare for adequate hedging strategy.

Fig. 3. Average debt to capital ratio.

5. Conclusion

This study assessed the efficiency of major cruise lines and identified the determinants of the efficiency. To this end, a network DEA model was built to elaborate the operation of cruise lines at two stages for the purpose of analyzing the financial statements of the lines: one for the operational and the other for non-operational. In the specification, cruise lines generate ticket revenue, other revenues, and operating income from their labor and capital resources at the operating stage. The operating income flows directly into the non-operating stage, which is closely associated with the financial activities of cruise lines that flow profits (net incomes) out of the operating income. Once the efficiencies of the lines were estimated by the DEA model, the determinants affecting the efficiencies were estimated using the bootstrapped-truncated regression.

The major findings are summarized as follows. First, major cruise companies performed generally well in their passenger operation. Their operation, however, was prone to epidemics as evidenced in tourism literature (Baxter & Bowen, 2004; Cooper, 2006). Next, the operating efficiency improved during economic crisis because cruise lines reduced their operating costs significantly. This interesting point is new in tourism literature, as existing studies (Papatheodorou et al., 2010; Smeral, 2010; Song & Lin, 2010) only highlighted indicators such as tourist counts. Another finding is that the non-operating efficiency of cruise lines varied widely, most likely due to their different financial strategies. Aggressive market followers, such as RCL and NCL, recorded low efficiency at the non-operating stage because of their high debt ratio, which put severe pressure on debt payments. This finding is similar to financial efficiency patterns in the other fields (Pires and Fernandes, 2012; Beck et al., 2013). In addition, though implicative, hedging strategies could also have affected the non-operational efficiency. For example, RCL and NCL adopted similar financial strategies in terms of the debt to capital ratio, but the non-operating efficiency of NCL was significantly different. This is because NCL failed to hedge against the interest rate and exchange rate, making it vulnerable to financial downturns. It is also noteworthy to see that economic downturn had detrimental effect on non-operating efficiency in general. Investment and capital utilization affected cruise lines net income critically, and even rigorous restructuring of operation could not make up for them.

This paper provides several managerial implications. First, epidemics affects the cruise lines' sales operation. To mitigate potential travelers' concerns on diseases, cruise lines need to ensure passengers that their service is clean and secure from epidemics. Media advertisement can be an effective tool to relieve potential travelers' worries. In addition, it would be helpful for cruise lines to reposition current operating routes to avoid tourist attractions

labelled as “epidemic zone.” The second implication is that cruise lines should prepare themselves for economic downturn, which poses great threat to earning net income. One way to cope with the shock is hedging. Active hedging against fuel costs (which accounts for the majority of operating costs) and insurance on idle capacity would be essential. Decision-makers should be aware that presumably wasteful spending on hedging in normal times can minimize significant loss during economic downturn. Another critical point is the capital investment. This strategy is essential for cruise lines to increase market share in the long run. The resulting debt burdens, however, can hurt the financial health of expanding cruise lines, leading to reduced net income and dividends for shareholders (note that NCL’s main source of non-operating inefficiency is high debt-to-capital ratio, which must have been mainly caused by aggressive capital investment). This can make investors hesitant to further investment, which in turn would increase the debt financing again. Hence, capital investment should be calculated by examining its negative impacts. When investing capital by debt financing, cruise lines should not hesitate to hedge against interest rate, fuel price, foreign currency, and other available hedging mechanisms. This would enable cruise lines to avoid sudden increases in liability (if interest rate gets high) and avoid the postponement of debt payment when the market condition is unfavorable.

This paper suggest a few directions for further study. First, if detailed information on hedging strategy of cruise lines becomes available, we can formally estimate the relationship between hedging and non-operating efficiency more quantitatively. Second, one can develop alternative network structures and recalculate the efficiency scores using other types of input and output sets. In this way, we can check whether the efficiency ranking among cruise lines are robust. Third, one can use dynamic DEA models to incorporate the inter-temporal influences between the years. Furthermore, since DEA efficiency measures are deterministic, some authors employed “bootstrapping” to draw confidence intervals for efficiency scores (Nguyen, Nguyen, Chang, Chin, & Tongzon, 2016; Wanke and Barros, 2016). The method would be beneficial in checking the robustness of DEA results in future research. Lastly, researchers can improve the method of handling negative output data, rather than substituting negative values by scaling down positive output values among observations, which this paper employed. To this end, researchers need to develop a network DEA model that captures the negativity of data in measuring inefficiency.

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