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E-mail emerald@emeraldinsight.com

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Guest editorial

**MABR special issue – shipping business strategy and risk management**

This special issue is gathered from selected papers of the 2017 Conference of the International Association of Maritime Economists, Kyoto, and independent papers submitted to the special issue. The theme of this special issue, *shipping business strategy and risk management* consists of topics in shipping asset management, cost management and optimization, freight derivatives, vessel portfolio strategy, shipping asset valuation and asset pricing mechanism. Its aim is to collect the latest research and practice on the processes of shipping business strategy and risk management. We would like to thank all authors for contributing to this special issue.

Shipbuilding and economic cycles is another interesting research question for the shipping business strategy and risk management. Mostly, the papers related to the economy and finance highlight the cyclical trends of different markets and their relations with the macroeconomic cycles. Shipping is one of those industries and it has often been characterized by peaks that influenced both the trade patterns and the industry investment structure. One of the main issues related to the cycles is the effect on overcapacity and prices for new building and how the understanding of these patterns can help in preventing shorthand strategies. Claudio Ferrari, Malvina Marchese and Alessio Tei investigate the shipbuilding cycles to get a distant signal and indications that can assist to investors for the investment strategy decision.

Financial bubbles have gained the substantial attention of academic researchers and industry over centuries. What characterizes a bubble is a rise in valuations of some types of assets, and the collapse of these valuations always cripples the economy and leads to subsequent pain. Thus, many economists make attempts to diagnose the formation of bubbles and to detect the bursting of bubbles ex ante, so that appropriate countermeasure can be taken in advance to reduce side effects arising from bubbles. The problem is however complicated. In a numerical study of Shun Chen, Shiyuan Zheng and Hilde Meersman applied Log-Periodic Power Law (LPPL) model to find out large market falls or “crashes” through modeling of the shipping price dynamics on a selection of three historical shipping bubbles over the period of 1985 to 2016.

Grace Wang, Qingcheng Zeng and Chenrui Qu investigate the complexity of the pricing strategies for the Chinese cruise value chain and incentive mechanism of cruise operation. Since the cruise operation in China is very different from two major cruise markets in the USA and the Mediterranean, they propose a particular optimization model by considering the game theory to provide market participants with strategies to enhance their decision-making processes. They designed effective strategies for attracting players participating in cruise value chain.

Increasing the autonomy of critical European seaports and harmonizing differences in the institutional governance between member states to create a more competitive environment could have a significant impact on the efficiency of the European maritime and multimodal transport system. Axel Merkel has focused on the relationship between the intensity of competition and technical efficiency for mainly the European market by using a stochastic frontier approach. To account for differences in governance structures and policy, five major port regions with diverse institutional features are compared. Using European
ports as objects of analysis is valuable because it can potentially yield findings relevant to the development and desirable direction for a harmonized policy framework. The results indicate that there is no significant adverse effect of competition on efficiency. In fact, for ports within a distance of 300 km, a higher level of competition is found to be associated with a higher level of efficiency. It appears that focusing efforts to reduce monopolistic powers of ports in local networks could be a viable way for policy to improve efficiency.

One of the significant issues in the container shipping is controlling risk for the operation under uncertainty. Son Nguyen and HaiYan Wang identified container shipping operational risks (CSORS) from a logistics perspective by considering fuzzy rules Bayesian network (FRBN). They define parameters that need to be considered to evaluate operational risks, and how to prioritize risks effectively under uncertainty in container shipping. Also, their proposed model can be used to measure a risk evaluation for different organizational scales.

Emrah Bulut
Yildiz Technical University, Besiktas, Turkey

Okan Duru
Nanyang Technological University, Nanyang, Singapore, and

T.L. Yip
Department of Logistics and Maritime Studies, Hong Kong Polytechnic University, Hong Kong
Shipbuilding and economic cycles: a non-linear econometric approach

Claudio Ferrari

*Italian Center of Excellence on Logistics Transports and Infrastructures, University of Genoa, Genova, Italy and Department of Economics, University of Genoa, Genova, Italy*

Malvina Marchese

*Department of Economics, University of Genoa, Genova, Italy, and*

Alessio Tei

*School of Engineering, Newcastle University, Newcastle upon Tyne, UK*

Abstract

**Purpose** – Economic studies have always underlined the cyclical trends of many industries and their different relations to the macro-economic cycles. Shipping is one of those industries and it has been often characterised by peaks that have influenced both the trade patterns and industry investment structure (e.g. fleet, shipyard activity, freight rates). One of the main issues related with the cycles is the effect on overcapacity and prices for newbuilding and how the understanding of these patterns can help in preventing short-hand strategies. The purpose of this paper is to evaluate different effects of business elements on shipbuilding activity, in relation to different economic-cycle phases.

**Design/methodology/approach** – This paper proposes a non-linear econometric model to identify the relations between shipbuilding and economic cycles over the past 30 years. The research focuses on identifying the cycle characteristics and understanding the asymmetrical effect of economic- and business-related variables on its development.

**Findings** – The study underlines the presence of an asymmetric effect of several business variables on the shipbuilding productions, depending on the cyclical phases (i.e. market expansion or economic slowdown). Moreover, lagged effects seem to be stronger than contemporaneous variables.

**Originality/value** – The paper is a first attempt of using non-linear modelling to shipbuilding cycles, giving indications that could be included in relevant investment policies.

**Keywords** Fleet development, Bulk shipping, Shipbuilding cycles, Shipping market

**Paper type** Research paper

1. Introduction

Starting from the works of Charemza and Gronicki (1981) and Sletmo (1989), several scholars underlined how the shipping industry (and shipbuilding) has been characterised by cyclical trends, normally discussed as simply connected to the economic cycle. Beenstock and Vergottis (1989a, 1989b) modelled the tanker and dry bulk markets including the influence of cyclical effects in their estimations, demonstrating the importance of cycles in different shipping industries. This well-discussed pattern – often included as one of the key industry characteristics in the main maritime economics textbooks (Stopford, 2009) – influences main developments in the shipping industry, determining a series of effects in operators’ strategies (Scarsi, 2007) and in the ship’s life (Bijwaard and Knapp, 2009).
Moreover, despite the definition of cycles applied to different industries is a well-known economic concept (primarily derived from the Kondratieff’s studies), its implications to the shipping-related markets have been seldom studied from a quantitative point of view, often focusing only at the shipping side of the maritime business. For instance, Guerrero and Rodrigue (2014) analysed the development of the container industry and its geographical diffusion linked to the macroeconomic trend. Yet they underlined how the long-term cycle in the maritime industry should always be linked to short-term effects that influence the specific trends within the industry. Similarly, Shin and Hassink (2011) focused their attention on the Korean shipbuilding cluster development, underlining the presence of a specific cycle that affected the recent market evolution. In fact, while macroeconomic elements affect the shipping industry in the long-term (50-year cycle), specific activities are also characterised by short-term cycles (3-7 years) in accordance with the business elements (Stopford, 2009; Klovland, 2002). Thus, macroeconomic variables (e.g. innovation, GDP) usually have an influence in longer periods, while business-related elements generate shorter cycles.

Figure 1 resumes the trends of both the economic cycle (GDP) from the 1980s and main shipping market indicators (i.e. Clarksea Index and Total bulk shipping order-book in DWT). The figure underlines both the volatility of the market and the cyclical path of all the studied variables. These trends affect main strategic ship-related decisions, such as the ship ordering time, freight rates and general market development.

Several authors (Bijwaard and Knapp, 2009; Knapp et al., 2008) underlined how this scenario affects the life cycle of the ship, having a direct effect on the shipbuilding market and on its development. In fact, as noted by many scholars (Shin and Hassink, 2011; Van Klink and de Langen, 2001; Stopford, 1987; Stopford and Barton, 1986) and industry reports, the shipbuilding industry heavily depends on the connected markets and the trends of the latter industries affect not only the overall performance of the shipbuilding operators but also their chances to survive in the market. Moreover, as noted by Audia and Greve (2006), the market structure and its trend increase the risk and the volatility of the big market operators, affecting the overall debt level and the probability to fail. As recently noted by

![Figure 1. Maritime trends](image)

**Source:** Own elaboration for Clarkson Database and OECD (2016)
main information channels (Tradewinds, 2016), often the degree of vertical integration of many shipyards – and their importance for the local economy – pushed national authorities to guarantee the survival of these operators, despite adverse market conditions. The importance of the link between shipbuilding cycles, economic trends and shipping development is then easily explained by the role that shipyards have for local economies. Moreover, the trend in increasing the ship size-pushed shipyards in expanding their construction capacity, having high fix costs that can be hardly recovered (or managed) in times of cycle downturn. For this reason having a clear picture of the cycle is a strategic issue within the maritime world.

Despite the importance of the abovementioned topic, several studies discussed the shipbuilding cycle, but few tried to apply econometrics techniques to understand the effects of the main economic- and shipping-related trends on the shipbuilding industry. The current study tries to fill this gap, using a novel approach to discuss not only the cycle but also the modification of the effect (i.e. the magnitude) that specific elements (e.g. steel price, world trade) in different phases of the economic cycle have on the shipbuilding market. Results will be then used to build policy advises to better understand future market trends.

The paper is organised as follows: after this brief introduction, Section 2 discusses the evolution of the shipbuilding market and its specific elements. Section 3 is dedicated to the discussion of the used data set, and Section 4 presents the applied methodology. Section 5 addresses analytical results, while Section 6 discusses possible business implications of the proposed analysis. Finally, Section 7 offers some conclusions and discussion of transport policy challenges arising from our results.

2. The shipbuilding market
The shipbuilding market has been recently characterised by a series of structural problems, mainly linked to the overcapacity that in the period of ship expansion of the early 2000s led to the construction of new shipyards, mainly in China. Grigorut et al. (2013) pointed out as the structural characteristics of the industry made it difficult to adjust to macroeconomic and business-related shocks, heavily affecting the capability of the shipyard supply to adapt to the changing market conditions. Thus, the shipbuilding market is characterised by high rigidity that makes market trends fundamental to rationally plan the needed investments. Despite this, recent events in Korea and China (Tradewinds, 2016) showed how recent investment did not take into account the effect of the business cycle, generating an unsustainable production capacity. Volk (1994) estimated that the variation in production within a cycle can be of about 50 per cent, generating drastic effects on the market that – as underlined by Solesvik (2016) – can only be mitigated through public intervention and, recently, exploitation of innovative practices. For instance, while in 2009 the world order-book accounted for more than 11,000 ships, in 2015, the order-book was of about 5,600 ships. Thus, the strict link between economic cycle and the shipbuilding business cycle has a strategic role for a sustainable planning of the resources. On this extent, while often the shipbuilding market is discussed as a homogenous sector, different subsectors can be identified. Thus, even in negative periods, different market segments may register positive trends (e.g. cruise, offshore support vessels). Despite this consideration, the main freight markets – in terms of number of ships and transported cargoes – have recently registered similar structural problems (i.e. liquid and dry bulk). Figure 2 shows the trend in fleet development (in terms of number of ships) and the related main transported cargoes (i.e. oil, oil products, iron ore, coal). Together with the growing
trend in a number of ships (with much higher rates than the transported cargos), the average disposable capacity has grown too, thanks to the introduction of ever bigger ships (e.g. very large ore carriers [VLOC] for the dry bulk sector) that strongly affected the market profitability.

Thus, while the overall number of ships and disposable shipping capacity generated an increased supply, the demand growth was not aligned with those trends. Thus, the immediate relevant effect was an increased investment in shipbuilding capacity (first years of the new millennium) followed by depressing trends for the shipbuilding industry. These generated a direct effect on the ship prices Figure 3 despite the necessity to cover the made investments. Furthermore, short-terms shocks, determined by both market circumstances (overcapacity) and macroeconomic trends, have generated the current shipbuilding situation.
2.1 Data collection

The abovementioned scenario leads to the necessity to better understand the shipbuilding market evolution to plan the strategic development of the related markets in a more sustainable way. Moreover, as noted for other sectors, the drivers of the shipbuilding industry may behave differently (i.e. with a different magnitude) in different cycle phases.

To identify the cyclical patterns, we collected various explanatory variables mainly through public available sources (e.g. OECD) and specialised databases (e.g. Clarkson). Our research focuses on the two main shipbuilding sectors per deployed tonnage (i.e. dry and liquid bulk). To perform the analysis, annual data from the 1970s have been collected but – given the necessity to collect different kinds of information for the two represented markets – the complete data set includes a complete time series starting from 1986 (until 2015). To determine economic cycles’ characteristics, the overall timeframe has been used (starting from 1976), and this was needed for the determination of relevant macro-economic phases. Moreover, the economic cycle is divided in two main phases: growing trend and decreasing trend. This division allowed us to differentiate the effect of single variables during the different phases of the economic cycles.

Therefore, in our model, both economic and business cycles are represented. Gross domestic product (GDP) is the main economic variable normally linked to the shipping market, while world trade has been also used to take into consideration the effect of the increasing international exchanges into the shipbuilding market (in particular iron ore trade [WSIO] for the dry bulk sector and oil trade for the liquid bulk [WSOP]). Concerning business-related variables, shipbuilding price, demolitions and overall saturation of the shipyards are the main variables. In particular, new shipbuilding prices (DNPI and TNPI depending on the reference market) and second-hand shipbuilding prices (DSHPI and TSHPI) will represent main business monetary elements that are traditionally linked to the strategic choice of buying a new ship. Moreover, they represent the market financial situation. Demolitions (TDD and TTD, for dry and liquid, respectively) are normally used as proxy to understand the complementarity in terms of a ship’s life cycle. Normally, demolitions are planned in phases of crisis (or to solve overcapacity issues), while they are postponed in times of market expansion. The overall order-book (DON and TON, for dry and liquid, respectively) is here used as proxy for market saturation and it should be pro-cyclical. The last considered variable is the steel price (SPI), as it represents the main production cost in the shipbuilding industry and it strongly affects the market performance. Understanding the effect of the cycle (and related variables) on the distribution of dry bulk fleet development (DFD) and tanker fleet development (TFD) represents the main goal of the current analysis. Because the decision of purchasing a ship is normally made months (and sometime years) in advance of the actual ship delivery, a lag of some decisional variable is added – using a proper estimation technique to assess it – to individuate also the lag in the decision-making process that affects the overall shipbuilding market.

3. Data set

Our data set consists of a time series of annual observations spanning from 1986 until 2015 (apart from the GDP for which quarterly data are used). Descriptive statistics for our variables are reported in Table I.

The distributions of DFD and TFD are skewed to the right and are fatter tailed than the Gaussian distribution. The Jarque–Bera test indicates rejection of the normality assumption.
for both variables, with $p$-values of 0.00167 and 0.001659, respectively, for dry bulk and tanker carriers. Bulk carrier production is the most volatile, exhibiting the highest positive skewness and excess kurtosis as well.

Figure 2 clearly shows that TFD has a noticeably lower growth rate than DFD, which displays a strong upward trend starting from 2005.

We test the stationarity of all the variables with the augmented Dickey–Fuller and Phillips–Perron tests, and for most of the variables, we cannot reject the null hypothesis of a unit root, which indicates significant evidences of non-stationarity. The GDP quarterly data are already differenced and appear fully stationary. We take difference of the other variables and investigate the relationship between the shipbuilding cycles (proxied by variations in dry bulk carrier and tanker production, respectively) and the economic cycles ceteris paribus. Figure 4 reports the autocorrelograms for DFD (top panel) and TFD (bottom panel).

Both series display a strong persistence across time: the LjungBox Q-statistics indicated rejection of the null hypothesis of no serial correlation up to the 20th lag for both. The partial autocorrelation function cuts off at lag one, suggesting an autoregressive process of the first order. We test for the presence of long-run persistence using the semiparametric Whittle estimator of Robinson (1995) and the Gweke–Porter–Hudak (GPH) log periodogram test. Both tests find that the fractional order of integration $d$ is close to zero, suggesting that a weakly dependent time series model is appropriate for the production series. Finally, we do not find any evidences of strong multicollinearity between the explanatory variables, and we are therefore, not concerned about inefficiency arising from this specification issue.

4. Econometric methodology

Our starting hypothesis is that the variation in the bulk carrier production is affected by the economic cycle and such an impact might be asymmetric according to business-cycle phases. The direct impact of GDP variations on dry bulk carrier and tanker production at different time lags can be identified by a simple Regime 1 dynamic lag model:

$$\Delta FD_t = \beta_0 + \rho \Delta FD_{t-1} + \beta_1 \Delta GDP_t + \beta_2 \Delta GDP_{t-1} + \beta_3 \Delta GDP_{t-2} + \alpha' x_t + u_t,$$

(1)
where $\Delta F D_t$ captures the annual variation in dry bulk carrier or tanker production from time $t - 1$ to $t$, $p$ is the autoregressive first-order coefficient and $X_t$ is the vector of all the control variables discussed in the previous section, with parameter vector $\alpha$. This model can be estimated by ordinary least squares (OLS) under the assumption of martingale difference and conditionally homoscedastic disturbances $u_t$. However it does not take into account the possibility that economics cyclical conditions may generate asymmetric effects, i.e. the impact of the explanatory variables on bulk carrier production over time is dissimilar in different phases of the cycle. Moreover it imposes linearity on the dynamics of the shipping production which might hinder important characteristic of the shipping cycles (Charemza and Gronicki, 1981).

In recent years, there has been considerable interest in modelling and testing for non-linearity in economic time series. Asymmetries over the business cycles have been modelled in the literature by means of regime-switching models, where the data-generating process is represented as a linear process that switches between a number of regimes according to some rule. Within the class of regime-switching models, two main categories can be distinguished, depending on whether the regimes are determined exogenously by an unobservable state variable, or endogenously by a directly

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**Note:** Top is dry carrier production variations, bottom is tanker production variations
observable variable. In Markov switching autoregressive (MS-AR) models à la Hamilton (1989), the transition between states depends on an unobservable state variable, generally modelled as a first-order Markov chain. In threshold autoregressive (TAR) models (often called sample splitting or segmented regressions) à la Tong (1986, 1990) and its extensions (Potter, 1995; Tiao and Tsay, 1991), the regime switching is governed by an observable variable, function of the data, possibly one of the equation regressors. Because this research wants to analyse whether the impact of GDP fluctuations on the shipping cycles is significant and different across business-cycle phases, the threshold variable is an observable business-cycle indicator and a TAR model is used. This methodology allows to model the probability of switching between regimes as endogenous and time variant rather than fixed, making forecasting more appealing.

Thus we consider a two-stage threshold model in the conditional mean, with structural equations:

$$
\Delta FD_t = \beta_0^{(1)} + \rho^{(1)} \Delta BFD_{t-1} + \beta_1^{(1)} \Delta GDP_t + \beta_2^{(1)} \Delta GDP_{t-1} + \beta_3^{(1)} \Delta GDP_{t-2} + \alpha^{(1)} x_t + \epsilon_t \Delta GDP_{t-d} \leq \gamma
$$

(2a)

$$
\Delta FD_t = \beta_0^{(2)} + \rho^{(2)} \Delta BFD_{t-1} + \beta_1^{(2)} \Delta GDP_t + \beta_2^{(2)} \Delta GDP_{t-1} + \beta_3^{(2)} \Delta GDP_{t-2} + \alpha^{(2)} x_t + \epsilon_t \Delta GDP_{t-d} > \gamma
$$

(2b)

The model is piecewise linear and it allows all the regression parameters to change depending on the value of the threshold variable. Each regime is characterized depending on the business cycles conditions, proxied by GDP variations, distinguishing between slowdowns (Regime 1) and expansionary phases (Regime 2). The parameter $\gamma \in [\underline{\gamma}, \overline{\gamma}]$ is the endogenous threshold, and $d \in [1, 3]$ is the discrete delay parameter. Equations (1) and (2) can be more compactly represented as:

$$
\Delta FD_t = (\theta^{(1)} z_t) I(\Delta GDP_{t-d} \leq \gamma) + (\theta^{(2)} z_t) I(\Delta GDP_{t-d} > \gamma) + \epsilon_t
$$

(3)

where $I()$ is the indicator function and $z_t$ is the vector of all the explanatory variables for $\Delta FD$ at time $t$, i.e. $z_t = (1, \Delta FD_{t-1}, \Delta GDP_t, \Delta GDP_{t-1}, \Delta GDP_{t-2}, x_t)^T$. We denote by $\theta^{(j)}$ the vector of all the regression equation parameters for Regime $j$, i.e. $\theta^{(j)} = (\beta_0^{(j)}, \rho^{(j)}, \beta_1^{(j)}, \beta_2^{(j)}, \alpha^{(j)}), j = 1, 2$. The errors are assumed to be a Martingale difference series with respect to the past history of $\Delta PB_t$. The parameters of interest are the coefficients $\theta = (\theta^{(1)}, \theta^{(2)})$, the threshold parameter $\gamma$ and the delay parameter $d$. Because Model (3) is a regression equation, albeit non-linear in the parameters, an appropriate estimation method is least square (Hansen, 1997). Under the additional assumption of normality of the disturbances, LS is equivalent to maximum likelihood estimation. Because both the threshold and delay parameters are unknown, we estimate the model with sequential conditional LSE using Hansen’s (1997) algorithm. We set $d \in [1, 2, 3]$, and for each value of $d$, we fix the threshold $\gamma = \Delta GDP_{t-d}$. We then run ordinary least squares on Model (3) for each value of $\gamma \epsilon \Gamma$, where the elements of $\Gamma$ are less than those of $T$ because a certain percentage
(η per cent) of observations must be taken to ensure a minimum number of these in each regime (henceforth let \( n \) denote the number of elements in \( \Gamma \)).

For any given value of \( d \) and \( g \), the OLS estimate of \( \theta \) is computed as:

\[
\hat{\theta}(\gamma(d)) = \left( \sum_{t=1}^{T} z_t(\gamma(d))z'_t(\gamma(d)) \right)^{-1}\left( \sum_{t=1}^{T} z_t(\gamma(d))z'_t(\gamma(d)) \right)
\]

and the sample variance of the residual as \( \hat{\sigma}^2(\gamma(d)) = T^{-1}\sum_{t=1}^{T} \hat{e}_t(\gamma(d))^2 \) with \( \hat{e}_t(\gamma(d)) = (\Delta PB_t - z'_t(\gamma(d)) \hat{\theta}(\gamma(d))) \).

For each value of \( d \), we find the estimates of \( g \) as:

\[
\hat{g}(d) = \min_{g \in \Gamma} \hat{\sigma}^2(\gamma(d))
\]

and compute the second-stage estimates of the coefficients as \( \hat{\theta}(d) = \hat{\theta}(\hat{g}(d)) \) and their sample variance as \( \hat{\sigma}^2(d) = T^{-1}\sum_{t=1}^{T} \hat{e}_t(d)^2 \) with \( \hat{e}_t(d) = (\Delta PB_t - z'_t(\gamma(d)) \hat{\theta}(\gamma(d))) \).

Finally the LS estimate of \( d \) are found as:

\[
\hat{d}_{LS} = \min_{d \in [\hat{d}, \bar{d}]} \hat{\sigma}^2(d)
\]

and the LS estimates of \( g \) and the coefficients as \( \hat{g}_{LS} = \hat{\gamma}(\hat{d}_{LS}) \) and \( \hat{\theta}_{LS} = \hat{\theta}(\hat{g}_{LS}) \). The minimization problem is solved by a direct search over \( nd \) regressions.

To verify if the starting assumption on the relation between shipbuilding cycles and business cycles is supported by the data, we wish to test weather Model (3) is a better statistical choice than Model (1). The null hypothesis is that the impact of macroeconomic conditions on bulk carrier and tanker production variations is constant during expansions and slowdowns, i.e. \( H_0: \gamma(1) = \gamma(2) \). This testing problem is not straightforward owing to the presence of unidentified nuisance parameters under the null hypothesis. Indeed under the null hypothesis, the model is linear, implying that the nuisance parameters \( d \) and \( g \) are not identified. If \( d \) and \( g \) were known, the statistic:

\[
F_T = \sup_{\gamma, d} F_T(\gamma, d)
\]

where \( F_T(\gamma, d) \) is the standard F-statistic:

\[
F_T(\gamma) = T\left( \frac{\hat{\sigma}^2 - \hat{\sigma}^2(\gamma, d)}{\hat{\sigma}^2(\gamma, d)} \right)
\]

where \( \hat{\sigma}^2 \) that denotes the residual sum of squares under the null hypothesis, would have near optimal power against alternatives, as \( F_T \) is a monotonic function in \( \hat{\sigma}^2 \), the residual sum of squares of the unrestricted model. Because \( \gamma \) and \( d \) are not identified, the asymptotic distribution of \( F_T \) is not a chi-square value. Hansen (1996) shows that asymptotic distribution can be approximated by a bootstrap procedure. We generate \( T \) random draws from a \( N(0,1) \) distribution \( u_i^* \) and define \( y_i^* = u_i^* \). Then \( y_i^* \) is regressed on the one-stage explanatory variables to obtain \( \hat{\sigma}^{*2} \), and on the two-stage explanatory variables to obtain \( \hat{\sigma}^{*2}(\gamma, d) \) and form:
\[ F^*_T(\gamma) = T \left( \frac{\sigma^* \gamma - \sigma^*(\gamma, d)}{\sigma^*(\gamma, d)} \right) \]

and

\[ F^*_T = \sup_{\gamma, d} F^*_T(\gamma, d). \]

Hansen shows that the distribution of \( F^*_T \) converges weakly to that of \( F_T \) under local alternatives to \( \theta \). Therefore we take repeated bootstrap draws from \( F^*_T \) to approximate the asymptotic \( p \)-value of the test by counting the percentage of bootstrap samples for which \( F^*_T \) exceeds the observed \( F_T \).

The standard diagnostic residuals test is no longer valid in the context of regime-switching models. To assess the presence of serial correlation or time series heteroscedasticity, we rely on their extensions as proposed by Li and Li (1996) and Li and Mak (1994) which are reported at the bottom of each estimated model. Rejection of the null denotes in all tests the presence of unexplained time series dynamics.

5. Empirical results

Tables II and III report the results for Regime 1 and Regime 2 threshold models estimated, respectively, for dry (Table II) and liquid bulk production (Table III) variations. Regime 1 captures economic cycles' slowdown, while Regime 2 represents the economic-cycle expansion phases.

Results for Model (1) confirm the well-known positive relation between GDP growth and variations in shipbuilding production, suggesting, however, that contemporaneous GDP variations have little, if any, impact, while lagged GDP variations, lagged back one and two years, are highly significant. The estimates also confirm the positive persistence of fleet development production across time for dry and liquid bulk carriers. This finding supports the lag in the decision-making process and a certain "path dependency" related to main strategic choices in the shipping industry.

The control variables display the expected signs: variations in steel price, total fleet demolition, order-book number and newbuilding price index negatively affect the shipbuilding production. Results show that the shipbuilding saturation level and the high input costs register anti-cyclical trends, while the demolition choice is normally directly connected with the possibility to prolong ship life if market conditions allow to do it.

Second-hand price index variations and seaborne trade of, respectively, iron ore and oil products, have a positive impact on fleet development production variations. Contemporaneous values of the explanatory variables display less significance than their lagged ones, suggesting that the dependent variables react to variations in the macroeconomic environment with one-year lag at the least. Thus, these latter variables show a timelier link with the dependent variable.

The one-stage models are, in the overall, significant, and do not suffer serial correlation or time series heteroscedasticity; however, their goodness-of-fit is quite low, with the adjusted \( R^2 \), respectively, at 0.116 and 0.138 for dry carriers and liquid carriers, suggesting that, while our choice of controls is statistically supported by the data, the model can be improved.

The estimates of Model (3) for both types of bulk carriers show that the impact of the business cycle on the shipping production cycle is subject to regime switches, which depend on the phase of the business cycle itself. It is evident that different business cycles
<table>
<thead>
<tr>
<th>Regime 1</th>
<th>(1)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.013***</td>
<td>0.026#</td>
</tr>
<tr>
<td>ΔBP1−1</td>
<td>0.761***</td>
<td>0.642***</td>
</tr>
<tr>
<td>ΔGDPt</td>
<td>0.011</td>
<td>0.015</td>
</tr>
<tr>
<td>ΔGDP1−1</td>
<td>0.531***</td>
<td>0.287**</td>
</tr>
<tr>
<td>ΔGDP1−2</td>
<td>0.485**</td>
<td>0.239**</td>
</tr>
<tr>
<td>ΔNBNi</td>
<td>-0.012</td>
<td>-0.034</td>
</tr>
<tr>
<td>ΔNBNi−1</td>
<td>-0.201**</td>
<td>-0.098**</td>
</tr>
<tr>
<td>ΔSPt−1</td>
<td>-0.007*</td>
<td>-0.171**</td>
</tr>
<tr>
<td>ΔSPI−1</td>
<td>-0.126**</td>
<td>-0.096***</td>
</tr>
<tr>
<td>ΔBSHPt</td>
<td>0.081*</td>
<td>0.099#</td>
</tr>
<tr>
<td>ΔTBDt</td>
<td>-0.005</td>
<td>-0.030</td>
</tr>
<tr>
<td>ΔTBDt−1</td>
<td>-0.021*</td>
<td>-0.056#</td>
</tr>
<tr>
<td>ΔWSIOt</td>
<td>0.023*</td>
<td>0.018</td>
</tr>
<tr>
<td>ΔWSIOt−1</td>
<td>0.612***</td>
<td>0.154**</td>
</tr>
<tr>
<td>ΔBSHt−1</td>
<td>-0.012</td>
<td>-0.017</td>
</tr>
<tr>
<td>ΔBONt−1</td>
<td>-0.207*</td>
<td>-0.133*</td>
</tr>
<tr>
<td>Regime 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>0.076*</td>
</tr>
<tr>
<td>ΔBP1−1</td>
<td></td>
<td>0.774***</td>
</tr>
<tr>
<td>ΔGDP1−1</td>
<td></td>
<td>0.326***</td>
</tr>
<tr>
<td>ΔGDP1−2</td>
<td></td>
<td>0.462***</td>
</tr>
<tr>
<td>ΔNBNi</td>
<td></td>
<td>-0.041</td>
</tr>
<tr>
<td>ΔNBNi−1</td>
<td></td>
<td>-0.167**</td>
</tr>
<tr>
<td>ΔSPt−1</td>
<td></td>
<td>-0.098**</td>
</tr>
<tr>
<td>ΔSPI−1</td>
<td></td>
<td>-0.101**</td>
</tr>
<tr>
<td>ΔBSHPt</td>
<td></td>
<td>0.036</td>
</tr>
<tr>
<td>ΔTBDt</td>
<td></td>
<td>-0.002</td>
</tr>
<tr>
<td>ΔTBDt−1</td>
<td></td>
<td>-0.093**</td>
</tr>
<tr>
<td>ΔWSIOt</td>
<td></td>
<td>0.011</td>
</tr>
<tr>
<td>ΔWSIOt−1</td>
<td></td>
<td>0.196***</td>
</tr>
<tr>
<td>ΔBSHt−1</td>
<td></td>
<td>0.231***</td>
</tr>
<tr>
<td>ΔBONt−1</td>
<td></td>
<td>-0.056</td>
</tr>
<tr>
<td>γ</td>
<td>NA</td>
<td>0.33**</td>
</tr>
<tr>
<td>d</td>
<td></td>
<td>1.000</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.116</td>
<td>0.853</td>
</tr>
<tr>
<td>LR test</td>
<td>NA</td>
<td>44.35***</td>
</tr>
<tr>
<td>$p$ value</td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td>$N_1$</td>
<td>NA</td>
<td>17</td>
</tr>
<tr>
<td>$N_2$</td>
<td>NA</td>
<td>23</td>
</tr>
<tr>
<td>η%</td>
<td></td>
<td>0.15</td>
</tr>
<tr>
<td>No. of bootstraps</td>
<td></td>
<td>1000</td>
</tr>
<tr>
<td>$Q_m(10)$</td>
<td>9.765 (0.665)</td>
<td>7.342 (0.324)</td>
</tr>
<tr>
<td>$ARCH(10)$</td>
<td>15.653 (0.876)</td>
<td>11.541 (0.546)</td>
</tr>
</tbody>
</table>

Notes: “This table presents the conditional LS estimates for the one- and two-stage models for dry bulk carriers and tankers. $\gamma$ is the estimated threshold, $d$ is the estimated delay parameter, $N_1$ and $N_2$ are the numbers of observations that lie in Regime 1 and Regime 2, respectively. LR is the likelihood ratio test for the null of the non-threshold whose $p$-value is computed through bootstrap. No. of bootstrap is the number of bootstrap replications used to compute the $p$-value. The trimming percentage $\eta$% is the percentage of observations that are excluded from the sample so that a minimal percentage of observations lies in each regime. The $Q_m(10)$ and $ARCH(10)$ test statistics and values reported are the standard ones for the Regime 1 model and their extensions by Li and Li (1996) for Regime 2 models; *statistical significance is 0.01; **statistical significance is 0.05; ***statistical significance is 0.1.”

Table II. Estimates for Regime 1 and Regime 2 threshold models for dry bulk*
### Table III.

Estimates for the Regime 1 and Regime 2 threshold models for liquid bulks

<table>
<thead>
<tr>
<th>Model</th>
<th>(1)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Regime 1</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.016**</td>
<td>0.021**</td>
</tr>
<tr>
<td>ΔTFD_{t-1}</td>
<td>0.481***</td>
<td>0.592***</td>
</tr>
<tr>
<td>ΔGDP_{t-1}</td>
<td>0.013</td>
<td>0.016</td>
</tr>
<tr>
<td>ΔGDP_{t-2}</td>
<td>0.278**</td>
<td>0.203**</td>
</tr>
<tr>
<td>ΔGDP_{t-2}</td>
<td>0.301**</td>
<td>0.178**</td>
</tr>
<tr>
<td>ΔTNPI_t</td>
<td>0.008</td>
<td>0.031</td>
</tr>
<tr>
<td>ΔTNPI_{t-1}</td>
<td>-0.198**</td>
<td>-0.082**</td>
</tr>
<tr>
<td>ΔTNPI_{t-2}</td>
<td>-0.059**</td>
<td>-0.056**</td>
</tr>
<tr>
<td>ΔSPI_{t-1}</td>
<td>-0.017**</td>
<td>-0.052**</td>
</tr>
<tr>
<td>ΔSPI_{t-2}</td>
<td>-0.046**</td>
<td>-0.086**</td>
</tr>
<tr>
<td>ΔTSHPI_t</td>
<td>0.073*</td>
<td>0.027</td>
</tr>
<tr>
<td>ΔTDD_t</td>
<td>0.005</td>
<td>-0.006</td>
</tr>
<tr>
<td>ΔTDD_{t-1}</td>
<td>-0.011*</td>
<td>-0.058**</td>
</tr>
<tr>
<td>ΔWSOT_t</td>
<td>0.031*</td>
<td>0.017</td>
</tr>
<tr>
<td>ΔWSOT_{t-1}</td>
<td>0.571***</td>
<td>0.072***</td>
</tr>
<tr>
<td>ΔWSOT_{t-2}</td>
<td>0.101***</td>
<td>0.119***</td>
</tr>
<tr>
<td>ΔTON_{t-1}</td>
<td>-0.009</td>
<td>-0.011</td>
</tr>
<tr>
<td>ΔTON_{t-2}</td>
<td>-0.201*</td>
<td>-0.128**</td>
</tr>
<tr>
<td><strong>Regime 2</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.0183**</td>
<td></td>
</tr>
<tr>
<td>ΔTFD_{t-1}</td>
<td>0.771***</td>
<td></td>
</tr>
<tr>
<td>ΔGDP_{t-1}</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>ΔGDP_{t-2}</td>
<td>0.679**</td>
<td></td>
</tr>
<tr>
<td>ΔGDP_{t-2}</td>
<td>0.578***</td>
<td></td>
</tr>
<tr>
<td>ΔTNPI_t</td>
<td>0.531*</td>
<td></td>
</tr>
<tr>
<td>ΔTNPI_{t-1}</td>
<td>-0.321*</td>
<td></td>
</tr>
<tr>
<td>ΔTNPI_{t-2}</td>
<td>-0.379***</td>
<td></td>
</tr>
<tr>
<td>ΔSPI_{t-1}</td>
<td>-0.129***</td>
<td></td>
</tr>
<tr>
<td>ΔSPI_{t-2}</td>
<td>-0.183***</td>
<td></td>
</tr>
<tr>
<td>ΔTSHPI_t</td>
<td>0.085*</td>
<td></td>
</tr>
<tr>
<td>ΔTDD_t</td>
<td>0.046</td>
<td></td>
</tr>
<tr>
<td>ΔTDD_{t-1}</td>
<td>-0.187*</td>
<td></td>
</tr>
<tr>
<td>ΔWSOT_t</td>
<td>0.013</td>
<td></td>
</tr>
<tr>
<td>ΔWSOT_{t-1}</td>
<td>0.169**</td>
<td></td>
</tr>
<tr>
<td>ΔWSOT_{t-2}</td>
<td>0.231***</td>
<td></td>
</tr>
<tr>
<td>ΔTON_{t-1}</td>
<td>-0.032</td>
<td></td>
</tr>
<tr>
<td>γ</td>
<td>NA</td>
<td>0.31***</td>
</tr>
<tr>
<td>d</td>
<td>1.001</td>
<td>0.837</td>
</tr>
<tr>
<td>R^2</td>
<td>0.138</td>
<td>53.78***</td>
</tr>
<tr>
<td>LR test</td>
<td></td>
<td>0.000</td>
</tr>
<tr>
<td>p value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N1</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td>N0</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>η%</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td>No. of bootstrap</td>
<td>1000</td>
<td>5.638 (0.337)</td>
</tr>
<tr>
<td>Qm(10)</td>
<td>7.987 (0.664)</td>
<td>9.876 (0.623)</td>
</tr>
<tr>
<td>ARCH(10)</td>
<td>13.256 (0.654)</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** *This table presents the conditional LS estimates for the one- and two-stage models for liquid bulk carriers and tankers. γ is the estimated threshold, d is the estimated delay parameter, N1 and N0 are the numbers of observations that lie in Regime 1 and Regime 2, respectively. LR is the likelihood ratio test for the null of the non-threshold whose p-value is computed through bootstrap. No. of bootstrap is the number of bootstrap replications used to compute the p-value. The trimming percentage η% is the percentage of observations that are excluded from the sample so that a minimal percentage of observations lies in each regime. The Qm(10) and ARCH(10) test statistics and values reported are the standard ones for Regime 1 model and their extensions by Li and Li (1996) for Regime 2 models; *statistical significance is 0.01; **statistical significance is 0.05; ***statistical significance is 0.1*
phases (i.e. slowdown or expansion) affect the magnitude and the significance of the
effects of the control variables on shipbuilding production. In particular, expansion
phases seem to generate increased “elasticity” to the dependent variables. The
likelihood ratio test for the null of no regime switch (i.e. symmetric responses to the
business cycle) is significant at any conventional level in both models, confirming the
appropriateness of threshold models and strongly supporting the hypothesis of
shipping production cyclicality. Furthermore the adjusted $R^2$ significantly improves
from the one-stage models, denoting a much better fitting in the overall (e.g. from 0.13
to 0.83 for the liquid bulk sector).

6. Business implications
Current research underlines different asymmetric effects of the economic cycle on the
shipbuilding production. It is important to underline that, one of the advantages of the
multiple-regime specification is that it allows endogenous estimation of the threshold
that determine the switch between an expansion and a declining phase. As shown in
Tables II and III, the value of the threshold is very similar for dry and liquid bulk
carriers, ranging between 0.31 and 0.33 per cent. This means that when the GDP growth
of the previous year is above these figures, the shipping production industry perceives
the economic cycle in expansionary phase and reacts accordingly. It is important to
notice that both thresholds represent positive values and are not connected to proper
recession phases; thus, the shipbuilding industry perceives economic slowdowns even
when GDP is still growing (even if at low rates). Moreover, the results show that the
shipping production industry reacts differently to changes in the macroeconomic and
industry-specific conditions during economic slowdowns (Regime 1) and expansions
(Regime 2). Indeed ship production tends to be more sensitive to variations in the
explanatory variables during expansions, demonstrating a certain proactive behaviour
in investing more than what needed in the long run. Similarly, in the slowdown phase,
the shipbuilding industry tends to avoid strong reductions in terms of production,
facilitating the generation of overcapacity. These latter elements could be connected to
the impossibility to stop the production facilities in which companies invested during
the expansion phase. In this regard, the presence of cluster authorities or the
involvement of government agencies (as done in Japan and, recently, in South Korea)
might help to better interpret market development.

Moreover, results demonstrate a persistence of the decision-making processes: main
studied variables have a lagged effect of about two years, demonstrating the need of a
proper planning in relevant production decisions. The fact that both business (e.g.
prices, traded cargo) and economic (e.g. GDP) variables tend to have effects in the long
run could be used as a signal for the industry strategic choices even if main production-
related facilities can be only slowed down and not definitely stopped. Nevertheless, the
possibility of estimating signals with different time periods could help shipyards better
evaluate their backlogs or identify proper tools to avoid overcapacity in the long run. It
is important to underline that the proposed model can be easily used to forecast future
market developments, helping practitioners to identify main market threats.

Another interesting finding that could help to better understand the shipbuilding
market development is related to the “opposite effect” of the ship prices: while
newbuilding price has a persistent negative effect, second-hand price seems to have a
short-term positive impact on the ship production. This characteristic is probably due
to the strong link between actual fleet production and price, while second-hand prices,
despite some literature statements, are more connected to the shipping market development than to the shipbuilding activity itself.

Eventually, it seems important to underline how liquid bulk and dry bulk sectors behave similarly: as also stated by Stott (2017), shipbuilding companies do not normally differentiate per market sector but per ship size. Thus, relevant cyclical effects are normally common for main ship categories, affecting the overall shipbuilding market in similar ways. Nevertheless, trade characteristics might affect the mix of ship order received by different shipyards and thus the differentiation seems to be connected to the possibility to attract new orders as well as to forecast market development in more accurate ways.

7. Conclusions
Previous research studies on shipbuilding cycles so far relied on linear econometric models and generally discussed the market trends considering the cycle as whole; this paper identifies the relation between economic and shipbuilding cycles and estimates the effect of main decisional and market-related variables on the shipbuilding production. Our most significant result is that the magnitude of the effects of different drivers of the shipbuilding industry varies depending on the economic cycle phase.

Thus, using a non-linear threshold approach, we found that variations in liquid and dry bulk carrier productions are significantly affected by the business cycles and that this impact is asymmetric across economic-cycle phases. Overall our results indicate that shipbuilding is strongly influenced by GDP variations in the previous two years. This result seems in line with main decisional process driving the shipping industry. Furthermore the impact of macroeconomics and shipbuilding industry-specific variables is pro-cyclical, implying that fleet development reacts more strongly during expansionary business-cycle phases. This factor seems of particular importance, as specific policy tools, aiming at rationalise shipbuilding supply and mitigate the market shocks, normally do not take into consideration different cycle phases. Nevertheless, the differentiated effects depending on economic phases might also imply the presence of a “bouncing back effect” that strongly encourage high investments in expansion times, making easier to register always more dramatic effects in time of recessions. This fact will be included in further analysis that will be elaborated starting from this preliminary results. Moreover, despite the different magnitudes in the effects, both studied sectors show similar trends, underlining how the shipbuilding sector reacts similarly independently on different ship production characteristics. As expected some of the production process-related variables (e.g. the proxy for the shipyard saturation) have an anti-cyclical effect, worsening the situation in case of a market slowdown.

Authors are aware of the limitation of the study (e.g. variable identification, presence of specific ship segments in the studied market) and further investigations will be devoted to the better understanding of specific factors or trade characteristics on the discussed findings. Eventually, the suggested model can easily be expanded to use it as a prediction tool, calibrating relative results with respect to the different sensitivity of the variables and related cyclical phase.

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**Corresponding author**
Alessio Tei can be contacted at: alessio.tei@ncl.ac.uk

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Abstract

Purpose – The occurrence and unpredictability of speculative bubbles on financial markets, and their accompanying crashes, have confounded economists and economic historians worldwide. The purpose of this paper is to diagnose and detect the bursting of shipping bubbles ex ante, and to qualify the patterns of shipping price dynamics and the bubble mechanics, so that appropriate counter measures can be taken in advance to reduce side effects arising from bubbles.

Design/methodology/approach – Log periodic power law (LPPL) model, developed in the past decade, is used to detect large market falls or “crashes” through modeling of the shipping price dynamics on a selection of three historical shipping bubbles over the period of 1985 to 2016. The method is based on a nonlinear least squares estimation that yields predictions of the most probable time of the regime switching.

Findings – It could be concluded that predictions by the LPPL model are quite dependent on the time at which they are conducted. Interestingly, the LPPL model could have predicted the substantial fall in the Baltic Dry Index during the recent global downturn, but not all crashes in the past. It is also found that the key ingredient that sets off an unsustainable growth process for shipping prices is the positive feedback. When the positive feedback starts, the burst of bubbles in shipping would be influenced by both endogenous and exogenous factors, which are crucial for the advanced warning of the market conversion.

Originality/value – The LPPL model has been first applied into the dry bulk shipping market to test a couple of shipping bubbles. The authors not only assess the predictability and robustness of the LPPL model but also expand the understanding of the model and explain patterns of shipping price dynamics and bubble mechanics.

Keywords Bubble modelling, LPPL model, Positive feedback, Shipping crisis

1. Introduction

Financial bubbles have gained substantial attention of academic researchers and industry over centuries. What characterizes a bubble is a rise in valuations of some types of assets, and the collapse of these valuations always cripples the economy and leads to subsequent pain (Filimonov and Sornette, 2013). Thus, many economists make attempts to diagnose the formation of bubbles and to detect the bursting of bubbles ex ante, so that appropriate counter measures can be taken in advance to reduce side effects arising from bubbles. The problem is however extremely difficult.
Superficially, financial bubbles are easily defined as transient upward acceleration of the observed price above a fundamental value, see Suzuki (1993), Shiller (2000), Kindleberger (2000), Sornette (2003, 2009), Shi (2005), Galbraith (1997), among others. The paradox is that the determination of a bubble requires a precise determination of what is the fundamental value. But the fundamental value is in general poorly constrained, so that it is not possible to distinguish bubbles from time-varying fundamentals. This drawback is however circumvented in studies of Johansen and Sornette (1999), Johansen et al. (1999), Johansen et al. (2000) and Sornette (2003), who propose the Log Periodic Power Law (LPPL) model, where a quantification is presented of the asset price dynamics leading up to a crash. The authors propose that a bubble is defined as a faster-than-exponential increase explained by the concept of positive feedback, see Sornette et al. (2013). When the positive feedback becomes dominant, the result is a self-reinforcing loop driving the market out of equilibrium. This loop continues until the bubble reaches its critical point. Based on this description, it seems possible to predict the bursting of speculative bubbles.

As regards the prediction of bubbles, Shiller (2000) is one among the few who have successfully predicted the bursting of bubbles ex ante, e.g. the crash of the dot-com bubble in 2000 and that of the housing bubble in 2007. However, Shiller and many others face the same fundamental drawback: using their methods they are unable to consistently and accurately predict the end date of a bubble (Gustavsson et al., 2016). The LPPL model provides a framework to detect bubbles and forecast their most probable end, reported by Sornette (2003). This approach has been applied to make a series of real-life tests and has been proven useful in predicting bubbles both ex post and ex ante in various markets, see Sornette and Zhou (2006), Sornette et al. (2009) and Zhou and Sornette (2003, 2005, 2008, 2009).

However, most previous studies present results that reinforce the theory, and only a few have highlighted both the potential and the limitations of the LPPL-model. The LPPL model is empirically appealing, as it provides a forecast of the date by which a financial crash might occur (Laloux et al., 1999). This is an important attribute relative to other methods of financial risk assessment. Furthermore, the LPPL model contains a component that captures the market’s excessive volatility prior to a crash. This feature is consistent with several theoretical models of financial crashes as well as with empirical results, see for instance Levy (2008) and Choudhry (1996). Gustavsson et al. (2016), who apply the model to time series of eight bubbles, chosen based on their historical context, argue as well that the predictions of the LPPL-model in most cases are quite accurate. The robustness, however, can be questioned, as the precision seems to be dependent on when they are conducted.

Furthermore, several critical considerations merit our attention associated with fitting an LPPL model to financial data. First, Johansen et al. (2000) show that the parameter estimates of the LPPL model are confined within certain ranges and that it is these ranges that are the indicators of market crashes. This approach considerably restricts the number of classes of permissible LPPL fits to just those fits with parameters that fall within the specified ranges rather than to LPPLs with any values for their parameters. Second, the mechanism underlying the LPPL model is such that prices must be expected to increase throughout the bubble, which is largely in line with the rational bubbles literature, instead of what has been found in early empirical fits of the LPPL model.

When it comes to the international dry bulk shipping market, it is widely accepted that this market, as the major component of the world shipping industry, has been recognized as highly risky and volatile, as it is subject to a number of uncertainties, ranging from geopolitical shocks and the ever-changing world economy to fleet changes and the sensitive market sentiment (Chen et al., 2014). During highly risky and volatile shipping market,
topics like the investment timing and market entry/exit decisions have attracted much attention of researchers, as the asset prices may vary enormously, see for instance, Alizadeh and Nomikos (2007), Bulut et al. (2013), Goulielmos et al. (2012) and Merikas et al. (2008). In particular, the exit before the burst of a bubble would be of vital importance for investors, as the burst of a shipping bubble will erode net worth and cause businesses to fail, touching off a devastating effect for both individual investors and the whole industry. Against this backdrop, the study on shipping bubbles counts for much.

Although the research on shipping bubbles remains one of hot topics for both researchers and practitioners, only a handful of studies qualify shipping bubbles when discussing investment timing or decisions [Barberis et al. (1998), Duru (2013) and Greenwood and Hanson (2014) among others], largely as a result of the difficulties in detecting, defining and quantifying bubbles in shipping market.

Barberis et al. (1998) explain shipping bubbles as the over-extrapolation of current profit levels. Merikas et al. (2008) introduce the relative price ratio between second-hand/newbuilding values as an investment indicator and the indicator of detecting shipping bubbles as well. Greenwood and Hanson (2014) analyze the value of Panamax second-hand vessels from 1976 to 2011 with their own intrinsic value measure, and bubbles arise when firms over invest during good times.

All of these studies center on qualifying and explaining bubbles, instead of quantifying them. It is the first time, to our knowledge, the LPPL model has been first applied into the dry bulk shipping market to test a couple of shipping bubbles. We not only assess the predictability and robustness of the LPPL model but also expand the understanding of the model and explain patterns of shipping price dynamics and bubble mechanics. The examination of shipping asset bubbles’ mechanics and the prediction of possible market regime switching, as a warning sign relating to market entry/exit, therefore, are of vital importance to both researchers and practitioners.

The remaining sections of this paper are as follows. Section 2 presents the model, the fitting procedure and the data. The empirical analysis of three bubbles in the dry bulk shipping market will be demonstrated in Section 3, and the final one summarizes the results.

2. Methodology

The LPPL model was developed to describe the dynamics of financial markets during bubbles and crashes. It is assumed that there are rational traders and noise traders who exhibit herding behavior that can destabilize the asset price (Filimonov and Sornette, 2013). In a bubble, the price undergoes certain oscillations that can reflect human grouping patterns (Sornette and Cauwels, 2015), and these social hierarchies manifest themselves in log periodic oscillations of the price with decreasing amplitudes, argued by Zhou et al. (2005).

These oscillations are superposed onto the super-exponential growth in a bubble. Super-exponential growth is however not sustainable and is bound to undergo a regime change before the singularity in finite time as an infinitely large price is not sensible in reality (Kaizoji and Sornette, 2010). The regime of unsustainable growth due to social imitation is described by the LPPL model.

2.1 The log periodic power law model

This model is first presented by Sornette et al. (1996) and the equation is defined as:
\[ p(t) = A + B(t_c - t)^\alpha + C(t_c - t)^\alpha \cos(\omega \log(t_c - t) + \phi) \]  

(1)

where \( p(t) \) is the logarithmic price at time \( t \), \( A \) is the value that \( p(t) \) would have if the bubble was to last until the critical time \( t_c \); \( B \) is the decrease in \( p(t) \) over the time unit before the crash if \( C \) is close to zero, and controls the growth rate of the magnitude. \( C \) is the magnitude of the fluctuations around the exponential growth as a proportion; \( t_c \) is the critical time; \( t < t_c \) is any time into the bubble preceding \( t_c \); \( \alpha \) is the exponent of the power law growth; \( \omega \) is the frequency of the fluctuations during the bubble; \( \phi \) is a shift parameter.

Filimonov and Sornette (2013) present a modification of the equation where they expand the cosine term of the original equation and rewrite the equation (1) as follows:

\[ p(t) = A + B(t_c - t)^\alpha + C_1(t_c - t)^\alpha \cos(\omega \log(t_c - t)) + C_2(t_c - t)^\alpha \sin(\omega \log(t_c - t)) \]  

(2)

where

\[ C_1 = C \cos \varphi \]  

(3)

\[ C_2 = C \sin \varphi \]  

(4)

The modification leads to two important implications, as explained by Filimonov and Sornette (2013).

First, the dimensionality of the nonlinear optimization problem is reduced from a four-dimensional space to a three-dimentional space. This significantly decreases the complexity of the problem.

Second, the cost function to be minimized now contains a single minimum instead of multiple minima, as long as the model is appropriate for the empirical data. The stability of the model is thereby significantly improved. Due to this transformation the need for complex search algorithms such as a taboo search is eliminated, and more simple algorithms, e.g. a Gauss–Newton algorithm, can be used without any reduction in the robustness of the estimation.

Taking into account all of these reasons, the methods in this article are based on equation (2) to investigate shipping bubbles.

2.2 Fitting procedure

Based on equation (2), there are four linear parameters (\( A, B, C_1, C_2 \)) and three non-linear parameters (\( t_c, \alpha, \omega \)). To reduce the fitting parameters, equation (2) should be rewritten simply as:

\[
\begin{align*}
  f(t) &= (t_c - t)^\alpha \\
  g(t) &= (t_c - t)^\alpha \cos(\omega \ln(t_c - t)) \\
  h(t) &= (t_c - t)^\alpha \sin(\omega \ln(t_c - t)) \\
  p(t) &= A + Bf(t) + C_1g(t) + C_2h(t)
\end{align*}
\]  

(5)

By using an estimate of the non-linear parameters, these four linear parameters can be solved via:
where \( y_i = p(t_i), f_i = (t_c - t_i)^\alpha, g_i = (t_c - t_i)^\alpha \cos(\omega \ln(t_c - t_i)) \) and \( h_i = (t_c - t_i)^\alpha \sin(\omega \ln(t_c - t_i)) \).

Then there are only three non-linear parameters needed to fit. As the chosen values of these parameters should be the ones that minimize the root mean squared error between the data and the predicted value of the model, the optimal function is:

\[
F = \sum \left[ A + B f_i(t_i) + C_1 g_i(t_i) + C_2 h_i(t_i) - p(t_i) \right]^2
\]

The generic algorithm is then adopted to fitting equation (7). The generic algorithm is a search heuristic that mimics the biological evolution process of natural selection and is routinely used to solve both constrained and unconstrained optimization problems. This algorithm is allowed to optimize parameters after encoding them into chromosomes without the limit constrains, and the search space starts at a set of problem solutions rather than a single individual with a characteristic of the parallel search. The solution with the best fitness, i.e. minimal optimal function, is taken as the solution.

The optimization procedure operates on the parameter space of the variables \( \alpha \) and \( \omega \), using a rolling window technique, as explained by Filimonov and Sornette (2013). In this article, we use a moving window \([t_1, t_2]\) with a length of 10 months, scanning the whole range of dates. The start and end date of the analyzed period is changed in between iterations, consistent with the recommendations of Sornette et al. (2013) to make the predictions more statistically robust.

The ranges of values given for both \( \alpha \) and \( \omega \) are based on the observed parameters of crashes for many stock markets (Johansen, 2003). \( \alpha \) must lie between 0 to 1, else we are dealing with some other types of process and not a power law characterized by the faster-than-exponential growth; \( \omega \) empirically takes on values between 3 and 15, see Johansen and Sornette (2010). Researchers tend to rely on established ranges for \( \alpha \) and \( \omega \), rather than any goodness-of-fit test, to identify the bubbles that precede crashes.

We constrain \( B \) to only take on negative values as well. In addition, we introduce constraints on the augmented Dickey–Fuller and Phillips–Perron values to filter out stationary fits which have no explanatory power in predicting the critical points, and only the non-stationary fits are accepted at a 1 per cent significance level (Gustavsson et al., 2016).

3. Empirical analysis

Shipping markets can be treated as a complex network of interacting traders. Under this theory, the aggregate behavior of all traders and investors can be modeled as a complex physical network. This network of traders transitions between the state of idiosyncratic behavior and herd behavior. During the state of irrational herd behavior, the shipping prices may demonstrate an exponential growth. When the market displays exponential growth, they may not always display signs of periodic oscillations of increasing frequency. These increasing periodic patterns only occur shortly before the rupture, or market crash.

In the dry bulk shipping market, there are three boom-burst cycles since 1980s, as proposed by Chen et al. (2014). Thus, the LPPL model is used to investigate the exponential growth of prices and the possible periodic oscillations of increasing frequency. In addition,
we examine as well the predictive ability of the LPPL model to forecast the burst of bubbles through modeling of price dynamics on a selection of historical bubbles. This paper fits parameters for daily logarithmic Baltic Dry Index (BDI) by making use of the LPPL model, based on a rolling window with a length of 10 months, as explained in the Section 2, Methodology.

The daily BDI is the weighted average of voyage rates and time charter rates on major trading routes by four major ship types of dry bulk carriers carrying a range of commodities including coal, iron ore and grain. It is the aggregate index and provides an assessment of the price of moving the major raw materials by sea. It can be served as an indicator of dry bulk shipping market and the world economy as well.

Since this index was first published on January 4, 1985, we check the time series of BDI and make an attempt to identify bubbles in the dry bulk shipping market over the period of January 1985 to November 2016. The trend of BDI can be observed in Figure 1. All the data were retrieved from Baltic Exchange. Descriptive statistics, shown in Table I, reveal that the mean values of logarithmic changes of the BDI are significantly different from zero. Both skewness and excess kurtosis are significant such that the Jarque–Bera test rejects the null of normality at a 1 per cent level.

We identify a peak as one initiating a crash based on the criterion proposed by Johansen et al. (2000). First, there exists a peak for which there is no value higher than the peak during the previous one trading year (262 weekdays); second, the price trend continues to increase in general for at least six months; third, the drop in price, a drop in price of 25 per cent, i.e. down to 0.75 of the peak price, needs to occur over a period of 60 weekdays.

![Figure 1. Trends of BDI over the period of January 4 1985 to November 20 2016](image)

<table>
<thead>
<tr>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>J-B</th>
</tr>
</thead>
<tbody>
<tr>
<td>BDI returns</td>
<td>8000</td>
<td>0.000027</td>
<td>0.015</td>
<td>0.113464</td>
<td>12.3773</td>
</tr>
</tbody>
</table>

**Notes:** • All series are measured in logarithmic first differences; • N is the number of observations; • Figures in square brackets [ ] indicate exact significance levels; • Skew and Kurt are the estimated centralized third and fourth moments of the data; their asymptotic distributions under the null are $T\hat{\alpha}_3/\hat{\alpha}_3\sim \chi^2(1)$ and $T(\hat{\alpha}_4 - 3)/(\hat{\alpha}_4 - 3)/24\sim \chi^2(1)$, respectively.
Based on this selection criterion, and due to the lack of previous thorough empirical examination, we select three bubbles to base our analysis upon: the bubble in 1995, when the shipping market was negatively affected by severe overcapacity; the bubble of 2004, when the market was heavily hit by the influx of massive fleet capacity growth and heavy deliveries, as well as the crash of 2007-2008, one of the most spectacular and speculative bubbles since 1970s.

Then the LPPL model will be used and the fitting procedure is translated into a code working in MATLAB to accurately predict the end of speculative bubbles through modeling of asset price dynamics on these three bubbles (matlab coding for the fitting procedure can be acquired from authors). Highlighted in dark gray in each figure of the subsections below is the 50 per cent confidence interval of the critical points \( t_c \), the results of the fitting procedure described above. The confidence intervals are plotted with the motivation that the date of the regime shift is a highly stochastic process and that the prediction of one specific crash date in fact might be misleading, and the 50 per cent confidence interval indicates the most probable period when bubbles are going to burst (Gustavsson et al., 2016). The median date of the critical points is marked in the corner of each figure and gives guidance to where it is more likely for the regime shift to occur. In each figure, the last observed date is illustrated as well, which indicates where the \textit{ex ante} prediction is assumed to be conducted.

In each graph, only a dozen of the resulting LPPL fits are plotted, regardless of how many resulting fits are produced. We do this for the sake of visibility, while the total number of fitted curves is given in the upper corner of each figure. Due to there, in most cases, being a lot of fitted curves we, instead of presenting the parameter values for each fit, present the parameter means based on all fits. These values are demonstrated for each estimation conducted one month prior to the peak.

### 3.1 Back test of the shipping bubble in 1995
The world economy moved into recession in 1992, but the dry bulk shipping market was not heavily influenced because it had not much burden from tonnage supply. After a brief dip freight rates recovered, reaching a peak in 1995. These years of relatively firm market had triggered heavy investment in dry bulk carriers leading to a huge orderbook, which went up to the peak in 1996. As deliveries were continuing up, the dry bulk market dropped since the second half of 1995 and moved into recession in 1996.

In this subsection, the time interval covers a moving window \([t_1, t_2]\) with a length of 10 months, as explained in the Methodology section. The initial starting date is \( t_1 = 4 \) March 1994, when the index was the lowest one year before the peak in 1995, while the end date \( t_2 \) runs form 13 January 1995 to 23 March 1995 in steps of five (trading) days. In these time intervals, the price of the index performed a faster-than-exponential increase. Means of parameters for LPPL equations can be found in Table II.

Figure 2 illustrates last three fitting results of a prediction conducted one month prior to the peak. The results are promising. The actual market peak date is 1 May 1995. The median is exactly the peak date, and the actual peak date is captured by the 50 per cent confidence

<table>
<thead>
<tr>
<th>Period</th>
<th>( A )</th>
<th>( B )</th>
<th>( C_1 )</th>
<th>( C_2 )</th>
<th>( \alpha )</th>
<th>( \omega )</th>
</tr>
</thead>
<tbody>
<tr>
<td>The bubble in 1995</td>
<td>7.9837</td>
<td>-0.0184</td>
<td>-0.00085</td>
<td>0.0021</td>
<td>0.6832</td>
<td>5.8664</td>
</tr>
</tbody>
</table>
interval. The dark shadow box in the figure indicates a nearly two-month range of the actual market crash date. It can be observed that last three predicted crash dates \( t_c \) lie in the range using only data before the market crashes.

3.2 Back test of the negative bubble from 2004
Since 2002, the world economy recovered and continued to grow rapidly. Stimulated by the sound growth of the world economy, the seaborne trade gained a consecutive annual increase, especially for shipments of main bulk commodities. One-year time charter rate for a Panamax soared from an average of \$7,499\ per day in 2001 to a historic peak in 2004. The buoyant freight market brought a rocketing increase of orderbook, achieving 67.8 million dwt in 2004 from 33.5 million dwt in 2000 (Clarksons Shipping Intelligence Network, 2016). The tremendous construction of new buildings since 2002 also gave rise to large deliveries from 2004, which dragged down the dry bulk shipping market.

The time interval window is rolling with an initial start date \( t_1 = 2 \) January 2002 with the end date \( t_2 \) increasing from 13 November 2002 to 4 January 2004 in steps of five (trading) days. Excluding stationary time series, 225 curves are produced by the model. In these time intervals, the price of the BDI performed a faster-than-exponential decrease. All the parameters can be seen in Table III.

From Figure 3, it is apparent that BDI prior to the slump in 2004 follows the characteristic pattern as proposed by the LPPL model; the prices seem to oscillate around a faster-than-exponential growth where the oscillations become smaller closer to the peak. These price movements act as they are expected to during a speculative bubble, according to

<table>
<thead>
<tr>
<th>Period</th>
<th>A</th>
<th>B</th>
<th>C_1</th>
<th>C_2</th>
<th>a</th>
<th>( \omega )</th>
</tr>
</thead>
<tbody>
<tr>
<td>The bubble in 2004</td>
<td>8.6990</td>
<td>-0.0477</td>
<td>-0.00219</td>
<td>-0.00193</td>
<td>0.5993</td>
<td>12.9406</td>
</tr>
</tbody>
</table>

Table III. Means of parameters for LPPL equations of predicting the bubble in 2004
the LPPL framework. It can also be seen from Figure 3 that the actual first peak date of February 4, 2004 is encapsulated by the 50 per cent confidence interval, and the median appears only 9 days ahead of the actual peak day. It implies that an *ex ante* estimation conducted one month prior to the actual peak date would have accurately predicted the upcoming change in regime.

3.3 Back test of the negative bubble from 2007 to 2008

Starting in 2005, the strong and sustainable growth of China, India and other dynamic developing countries was increasingly becoming the main driver of the world economy. China’s GDP growth remained above 10 per cent from 2003 and gained a record high of 11.5 per cent in 2007. The seaborne trade of dry bulk shipping slowed down significantly in the wake of a globally gloomy economy and a lack of demand for steel. On the supply side, ship owners have ordered massive tonnage during the shipping boom since 2004, and the market was seriously hit by massive deliveries. The total dry bulk fleet in 2012 was 615.5 million dwt, increased by about 130 per cent since 2000. Resulting from both sluggish demand and surplus of tonnage, charter rates of dry bulk vessels plummeted and so did ship values of both second-hand and newbuilding vessels. For example, one-year timecharter rate for a Panamax dripped from a record high level of $71,500 per day in 2007 to an average of $4,350 per day in 2012 (Clarksons Shipping Intelligence Network, 2016).

When fitting the LPPL equation to the time series preceding the peak we arrive at the results presented in Figure 4. The time interval window is rolling with an initial start date $t_1 = 25$ January 2006 with the end date $t_2$ increasing from 6 December 2006 to 10 October 2007 in steps of five (trading) days. In these time intervals, the price of the CSI300 index performed a faster-than-exponential decrease.

It can be seen from the figure that the indices during this period follow the characteristics of LPPL. It can also be seen from Figure 4 that the 50 per cent confidence interval captures the actual peak date, or regime shift of 13 November 2007, while the median date is only six days later. This means that if an *ex ante* prediction would have been performed on the Baltic indices one month prior to the actual peak in 2007, it would have given us a good estimation of the upcoming date of the regime shift (Table IV).
3.4 Testing the robustness of the model

In testing the robustness of the model, we proceed by changing several parameters or conditions and see whether there is any distinct difference in results. First, we test the influence of the last observed date on the robustness of the model by setting the last observed date two months and two weeks prior to the actual peak, respectively, and repeat the estimation process. Second, we change the length of the rolling window to be 15 months, increased from 10 months. Here, we only present results of making the comparative analysis conducted in the case of predicting the bubble in 2007, and results of the others can be acquired from authors.

When performing an estimation where the last observed date is two months prior to the peak, we reach similar results to those of Figure 4. It can be seen from Figure 5(a) that the median date is shifted four days to the left in the graph, while the confidence interval is slightly broadened compared to the first estimation of Figure 4. These results indicate that an ex ante prediction conducted two months prior to the peak would have yielded almost the exact same conclusions regarding the upcoming regime shift as those of the estimation performed one month prior to the peak. However, the broadened confidence interval indicates some additional uncertainty, which is expected when performing an earlier ex ante prediction.

From Figure 5(b), where the last observed date is set two weeks prior to the peak, it is evident that both the confidence interval as well as the median are shifted a couple of days later compared to the estimation of Figure 4. As the LPPL framework suggests that the

<table>
<thead>
<tr>
<th>Period</th>
<th>A</th>
<th>B</th>
<th>(C_1)</th>
<th>(C_2)</th>
<th>(\alpha)</th>
<th>(\omega)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The bubble in 2007</td>
<td>9.4575</td>
<td>-0.0436</td>
<td>-0.00263</td>
<td>0.00239</td>
<td>0.5923</td>
<td>9.3734</td>
</tr>
</tbody>
</table>
regime shift should occur when the oscillations reach zero, one possible explanation for this behavior could be that the amplitude of oscillations is already quite low when the predictions are conducted. The confidence intervals will continue to move to the right in the graph when moving the last observed date to the right, as long as the oscillations soon after the last observed date are close to zero.

This means that estimations performed two months and two weeks prior to the actual peak day would have yielded similar conclusions regarding the upcoming change in regime.

Figure 5.
(a). The LPPL model fitted to BDI prior to the bubble in 2007 with the last observed date two months prior to the peak day
(b). The LPPL model fitted to BDI prior to the bubble in 2007 with the last observed date two weeks prior to the peak day
Results that are largely unaffected by when the predictions are conducted are what one wishes to see when examining a bubble.

In Figure 6, the LPPL equation is fitted to Baltic indices one month preceding the downturn of 2007 based on the rolling window of a length of 15 months. It is apparent that the indices follow the characteristics of LPPL. It is also evident that the predictions of the LPPL model in this case produce similar results as those obtained based on the first estimation of Figure 4. The confidence interval is slimmer, but the actual peak day on 13 November is still captured.

4. Further discussion

In our study, the actual peak date is not known when conducting *ex ante* predictions, and the date of the regime shift is a stochastic process; therefore, the prediction of the bursting of a speculative bubble at one critical point may be misleading. Instead of looking at estimation of one crash time, we make an attempt to estimate a period when the bubble will burst at certain confidence intervals. The timing of crash can happen in the middle of, immediately after or long after this estimated period, although our empirical results exhibit the capture of actual peak days within the 50 per cent confidence interval.

4.1 Findings relating to the model

The period of predicted end dates of a bubble, in this way, should be interpreted as the start of a period when the market becomes more sensitive to negative external events, which is consistent with the analysis by Gustavsson *et al.* (2016), who propose that the model’s ability to predict the bursting of bubbles is not as strong as has been claimed in previous studies, and the results of all estimations have to be interpreted in a more careful manner.

Second, the theory of the model only applies to bubbles that are driven by the endogenous factors of the LPPL framework and does not claim that all bubbles follow this pattern, see Johansen and Sornette (2010). In reality, factors triggering a bubble are complex, which may be not only driven by endogenous super-exponential growth but also by other factors. In this case, we propose that the LPPL model may not be enough to explain and
predict the end of a speculative bubble in some cases, where exogenous shocks may have
significant influence on the burst of a bubble.

For example, we can see two peaks during the period of 2007-2008. The burst of the
bubble in November 2007 was followed soon by the outbreak of the financial crisis occurring
in the USA, which can be deemed as a critical exogenous factor to the market. It is argued by
Gustavsson et al. (2016) that if such an exogenous event occurs before the speculative
behavior has reached maturity, the price will not fall drastically as they are not sufficiently
overvalued to begin with. A dip in prices can be expected as they are affected by exogenous
shocks, and the index quickly returns to the trend and thereafter continues to rise. The
downturn in early 2008 was trigged by an unsustainable faster-than-exponential growth of a
bubble and the negative credit crisis spread all over the world.

We have already observed that the 50 per cent confidence interval and the median are
shifted as the last observed date is changed. It indicates that the time series is sensitive to a
regime shift just following the last observed date, so that the regime could be influenced
significantly by both exogenous and endogenous factors.

Third, it is evident from all figures that the oscillations decrease in amplitude as the
bubble approaches its regime shift. The possible explanation for this could be the results of
diverse investors’ psychology and investment actions. When the market reached a record
peak, it is argued that investors get more anxious, and they are less confident of the future
movements of the market, while at the same time, some believe the market continues to
increase and are afraid of missing out on further increases. Heterogeneous views of the
market and investment strategies of market participants result in frequent trading actions of
sell-outs and buy-ins over a short period, leading to more frequent oscillations with lower
amplitude as the bubble gets older.

4.2 Economic explanations of bubbles
It is demonstrated by the empirical analysis that during three bubble phases, the price index
follows a faster-than-exponential power law growth process, accompanied by log periodic
oscillations. When resources are unlimited, exponential growth can go on indefinitely. This
is different in systems of finite size, where there is competition for limited resources
(Sornette and Cauwels, 2015). When the resources are not unlimited, prices will follow an
unsustainable track, bringing the market to a critical state characterized by the existence of
an intrinsic end-point.

The key ingredient that sets off an unsustainable growth process, which is a prerequisite
for a financial bubble, is positive feedback. Positive feedback is often caused by imitation:
when investors display herd behavior, a price increase triggers even greater demand due to
the strengthening of the herd, and consequently, the equilibrium of supply and demand
breaks down.

In the dry bulk shipping market, smart money flows in at the early stage when the
market is picking up, which leads to a first wave of price appreciation. Attracted by the
prospect of extrapolated higher returns, more investors follow. At some point, demand goes
up as the price increases, and the price goes up as the demand increases. This is a positive
feedback mechanism, which fuels a spiralling growth away from equilibrium. The positive
feedback before bubbles in the dry bulk shipping market could be revealed distinctly by
Figures 7-9 (the dry bulk shipping market is generally divided into three sub-markets by
ship size: the Capesize, the Panamax and the Handymax/Handy markets). Before crashes in
the year of 1995, 2004 and 2007, the dry bulk shipping market was booming, witnessed by
the sharp hike in the second-hand ship market. When second-hand ship prices go up, orders
for new vessels pick up, together with the increasing volume of second-hand ship sales.
Testing for the burst of bubbles

Figure 7. Second-hand ship sales, prices and orderbook percentage in the capesize market

Figure 8. Second-hand ship sales, prices and orderbook percentage in the panamax market

Figure 9. Second-hand ship sales, prices and orderbook percentage in the handymax market
The process of positive feedback operates not only directly from past price increases but also from auxiliary psychological changes of investors that the past price increases helped generate. As prices continue to rise, the level of exuberance is enhanced by the price rise itself. Investors, their confidence and expectations buoyed by past price increases, bid up ship prices or freight rates further, thereby enticing more investors to do the same, so that the cycle repeats again and again.

Investors buy and sell ships in anticipation of future market prices, but those prices are contingent on the investors’ expectations. Investors are striving to do the right thing, but they have limited abilities and certain natural modes of behavior that decide their actions when an unambiguous prescription for action is lacking. In the absence of knowledge and unlimited abilities, participants must introduce an element of judgment or bias into their decision-making. As a result, outcomes are liable to diverge from expectations.

5. Conclusions
The aim of this study is to analyze the predictive ability of log periodic functions which, according to some researchers (Sornette and Zhou, 2006; Sornette et al., 2009) can be used to forecast accurately turbulent changes of certain phenomena, such as the changes observed on the financial markets.

The evaluation of this method’s accuracy is based on three log periodic models constructed for the evaluation of Baltic index behavior over different periods. The objective is to predict the bursting time of shipping bubbles’ occurrence. We find that all the bubbles analyzed (the bubble in 1995, the bubble in 2002 and the crash in 2007) behave in accordance with the expected characteristics of the LPPL model. The price movements leading up to the regime shift are characterized by faster-than-exponential growth and show clear oscillatory patterns where the oscillations decrease in amplitude leading up to the regime shift. In our analysis, actual peak dates are encapsulated by the confidence intervals of critical points, bolstering the argument that the model has the good predictive ability.

However, we also observe in some cases that the index continues to rise with small oscillatory patterns even after the predicted regime shifts. Furthermore, the comparative analysis by changing the last observed dates and the number of estimations for each bubble implies that the LPPL model may be sensitive to the time when the predictions are conducted and sensitive to the number of estimations for each prediction. In this way, to predict one crash date may be misleading when conducting the ex ante prediction, and to produce a period of critical points within some confidence intervals is more reliable.

It is worth noting from this paper that fitting the model into historical data and using it to generate prediction in real time are two different things and the latter is much more difficult. The LPPL model is only applicable to the bubble driven by endogenous factors, while in reality, exogenous shocks could have significant influence on bubbles.

In considering the economic triggers for bubbles in the shipping market, to speak of supply and demand as if they are determined by forces that are independent of the market participants’ expectations is quite misleading. Rising ship prices often attract buyers and vice versa, as evidenced by rising ship sales. The self-reinforcing trends cannot persist if supply and demand curves are independent of market prices. Hence, market investors’ expectations could also behave as one of fundamentals when the positive feedback mechanism works.
Thus, it is not enough to just rely on this model to guide our investment decisions, more analyses are needed, such as the fundamental study, the exogenous factors/news influencing the dry bulk shipping market.

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Further reading

Corresponding author
Shiyuan Zheng can be contacted at: syzheng@shmtu.edu.cn

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A game theory application of a cruise value chain – the case of China

Grace W.Y. Wang
Department of Maritime Administration, Texas A&M University at Galveston, Galveston, Texas, USA

Qingcheng Zeng and Chenrui Qu
School of Transportation Management, Dalian Maritime University, Dalian, China, and

Joan Mileski
Department of Maritime Administration, Texas A&M University at Galveston, Galveston, Texas, USA

Abstract

Purpose – Regardless of the facts showing a booming Chinese cruise market, cruise operations in China are very different from the current practices of the two major cruise markets – the US and the Mediterranean Sea. This study aims to quantify pricing strategies and possible incentive mechanisms of cruise operations in China.

Design/methodology/approach – Using optimization in economic-based game theory, the complexity of the pricing strategies and interaction and/or possible coordination within the cruise value-added chain can be captured.

Findings – The results show that a coordinative pricing strategy with Shapley profit redistribution within the value-added chain offers benefits to both cruise passengers and service suppliers. With two subsidy scenarios, one to the passenger and the other to the travel agent, a cooperative pricing strategy outperforms other strategies and successfully increases market shares and total revenue.

Originality/value – The advantages of coordination between participants in cruise value chain are quantified. Effective strategies for attracting players participating in cruise value chain are designed. This paper will provide market participants with strategies to enhance their decision-making processes.

Keywords Game theory, Vertical integration, Cruise supply chain, Port subsidy, The benefit distribution

Paper type Research paper

1. Introduction

The cruise industry is considered one of the fastest growing segments in the shipping industry. Cruise lines with extended off/onshore activities along with entertainment on board provide extraordinary experiences to customers in keeping with the sustainable long-term growth of the tourism. Since 1980, the cruise ship industry has experienced a passenger growth of 7.2 per cent annually. The number of cruise passengers across the world has
increased from 15.62 million in 2007 to 23 million in 2015 (Florida-Caribbean Cruise Association FCCA Cruise Industry Overview 2015).

The Cruise Line International Association has published a recent report showing Asia cruise trends show a booming Asian market. In between 2013 and 2016, there is a 12 per cent growth in the number of ships deployed in Asia, 22 per cent growth in the number of cruises and voyages within Asia, 13.6 per cent expansion in annual operating days and 29.3 per cent increase in annual passenger capacity. Even though the cruise market in China is considered a relatively new form of recreation, China is the driver of passenger growth in Asia, adding 770,000 more cruise travellers, creating a 66 per cent annual growth rate in 2012. In 2015, China has provided approximately 1.1 million passengers, with 986,000 passengers coming from mainland China. Growing business can be observed from the increased frequency of calls, new facility terminals, various travel packages with unique shore excursions, different destinations, activities such as barge trip, kayaking and better rail and road connections. Currently, there are seven cruise lines operating 12 cruise routes in Asia. Growing business in terms of new entrants of cruise companies with similar services and packages has created fierce competition for the cruise market.

Regardless of the facts showing a booming Chinese cruise market, cruise operations in China are very different from the current practices of the two major cruise markets – the USA and the Mediterranean Sea. In the USA, major cruise companies operate under an oligopolistic market structure. Cruise companies negotiate the contracts with the cruise ports for terminal and facility usage, dedicated services and/or connection to ground transportation and parking with considerable bargaining power. Often times, cruise ports provide incentives to the cruise companies in exchange for a longer operating contracts, more frequent number of calls or a greater number of passengers. Without sufficient incentives, cruise companies can easily reduce or move operations and leave the cruise ports hanging. However, this is not the case in China. Specialization of cruise operation in Chinese ports can rarely be seen. Major ports may have one or two multipurpose terminals that can handle cruise operations. With limited physical space for cruise terminals, ports that are willing to serve cruise lines have more bargaining power than the cruise companies that differ from the US and the Mediterranean. The ports dominate the game in selecting which cruise lines will be served with which cruise facilities and cruise terminals, as well as determining the frequency of calls by each cruise line. That means the typical pricing and/or cooperation models applied to the USA and Mediterranean Sea may not be suitable for China.

Another interesting fact comes from the regulatory side. In the USA, customers who are interested in going on a cruise have multiple alternatives from which to choose when purchasing a cruise package. They can use online booking from the cruise line’s official websites and/or from the popular travel webpages, such as Expedia and Travelocity. They can also use a travel agent who offers personalized advice with a variety of combined packages of ship types, itineraries, dining plans and cabin selections. Depending on the customer’s needs, booking online or through travel agents has its own pros and cons but the option remains available for the cruise passengers. However, in China, there is no direct booking mechanism. Customers must find a travel agent. This affects cruise line’s pricing and market strategies.

Given the uniqueness of the Chinese cruise operations with the ports they serve, we tailor a game theory model to demonstrate the interaction of key players in the cruise line value-added chain in a quantitative game theory. The features unique to the Chinese cruise market include the following:
- Cruise port dominates the game in selecting which cruise lines can use the port, its facilities and its terminals, as well as determine the frequency of calls that the cruise line can make at the port.
- No direct access for cruise passengers to book and/or arrange itinerary from the online travel sites. Cruise travelers must go through travel agency to book and/or purchase pre-determined packages.

Value chain or value-added chain analysis is applied to assess the relationship between different economic drivers within a given scope of a product or service. While the scope of the value chain application could be as small as the various stages of a production line served within a firm, it can be broadly defined as seen in the marine sustainability and agricultural applications (Irvine, 2015). “A broad approach to value chain analysis starts from the production system of the raw materials and moves along the linkages with other actors and enterprises engaged in trading, processing, assembling, transporting, etc. This broad approach examines all of the activities of a single enterprise, as well as all of the backward and forward linkages from the raw materials to final consumer” (Rosales et al., 2017). Revisiting the complete value-added chain in cruise line recreation includes cruise passengers, crew, travel agencies, cruise lines and cruise ports; the biggest challenge for the cruise industry is to offer the best experience for passengers in a constantly changing environment that requires quick response to provide high-quality services. Thus, the cruise value-added chain integrates the various upstream and downstream business operations.

Generally speaking, the value-added chain in cruise recreation is company oriented. The upstream firm/customer coordination covers passengers and the cruise port, whereas the downstream cooperation includes the travel agency. An efficient and undisrupted production chain can improve the quality of the cruise services and the individual competitiveness of the value chain members in the entire system. However, conflict of interests exists between the members of the chain. Lack of cooperation and cohesion may lead to inefficiency along the entire value chain. Hence, the key to the cruise value chain management lies in the mechanism appropriate distribution of the profit among the members. One way to do that is through a properly structured pricing strategy. Various pricing strategies used by cruise companies can increase profitability and improve occupancy rate. Efficient allocation of resources in the value chain can reduce operating costs. In this study, we quantify pricing strategies and possible incentive mechanism in the Chinese cruise business operation. With an economic approach using optimization in the game theory, the complexity of the pricing strategies and interaction within the cruise value-added chain can be captured.

What we find is that coordinative pricing strategy with Shapley profit redistribution within the value-added chain offers benefits to both cruise passengers and service suppliers. With two subsidy scenarios, one to passenger and the other to travel agent, cooperative pricing strategy outperforms individual pricing strategies successfully increasing market shares and total revenue. With the integrated upstream and downstream structure, the model can further be extended to examine under what circumstance the vertical integration and/or coordination of a cruise supply chain can improve performance for all in the value-added chain, such as cruise ports, cruise companies and relevant service providers. Likewise, the model can be used to compare the differences in current cruise pricing strategies and practices in different continents. However, vertical integration and cooperative pricing strategies in some market such as the US and Europe are subject to anti-trust evaluation, so not every pricing strategy purposed for China will be available in those markets.
2. Literature

The cruise industry scholarly research increased recently. Studies can be found from a broader scale of demand and supply for cruise tourism, routing of cruise vessels and the economic impacts of cruise activities (Petrick and Li, 2006; Dwyer and Forsyth, 1998; Dwyer et al., 2004; Chang et al., 2016). Regional studies from either the port’s perspectives or from the passenger’s perspective is another stream of literature (Brida et al. (2013) for the Port of Cartagena, Colombia; Wang et al. (2014) for the East Asian ports, Castillo-Manzano et al. (2014) for Spanish ports, Esteve-Perez and Garcia-Sanchez (2015) for the Mediterranean ports and Sun et al. (2014) for Chinese ports.

The focus of this study is to provide a theoretical framework to showcase the features of Chinese cruise operations. At the same time, through a conceptual value-added chain, a guideline of a practical efficient pricing strategy that eventually leads to the best reallocation and redistribution of profit within the chain is reached. Local agents in the destination could generate tremendous added value for the whole cruise supply chain (Gui and Russo, 2011). This is a natural way for cruise lines to develop more efficient cruise chains involving local agents with intimate knowledge of the operation and regulation, and environment at the local destination (Veronneau and Roy, 2009). Many researchers have studied the integrated transport chain formed by the cooperation of multi-stakeholders upstream and downstream, e.g. Asgari et al. (2013); Clott and Hartman (2016) and Song et al. (2016). Firms turn attention to incremental value created from the coordination within the intricate network instead of holding separate function (Min and Zhou, 2002). When considering the fierce competition for shipping demand, competitive advantages of supply chain collaboration have been identified. Customer value created through the supply chain has successfully caught the attention of those in the discipline of value chain management, along with the concept of managing integrated services from suppliers to the end-customers for economic sustainability and high efficiency of the entire value chain (Fearne et al., 2012).

Pricing strategy is important especially in the cruise industry. Service price is negatively related to customers’ value perception of the cruise experience (Blas and Carvajal-Trujillo, 2014; Chua et al., 2015). It is quite critical for stakeholders in the supply chain to adopt effective pricing strategy on customers’ perceived value. (Al-Mudimigh et al., 2004; Christopher and Gattorna, 2005). With semi-structured interviews to study Chinese tourism, Sun et al. (2011) reviewed revenue management in cruise industry comparing the differences between cruise lines and hotel revenue management. For example, each customer is priced separately and served by a travel agent in the cruise industry. That difference limits the scale of the traditional hotel pricing theory and it may not be able to be successfully applied to cruise industry. Ladany and Arbel (1991) proposed an optimal price discrimination policy to help cruise companies identify and extend potential markets. Based on the distinction of market segments between price-sensitive and price-insensitive customers, the competitive advantages of price discrimination strategy in cruise industry are investigated by Langenfeld and Li (2008). Comparative analysis is used to evaluate the effects of price discrimination and uniform prices on output and profit of cruise lines. Moreover, price discrimination strategy could bring considerable benefits to cruise lines with limited competition. Similarly, Petrick (2005) studied the discount pricing strategy to attract cruise passengers, and showed that price-sensitive passengers do respond positively to those marketing strategies and have a relatively positive cruise experience.

Discounts also affect the cruise customers’ view of the cruise experience. Duman and Mattila (2004) pointed out that experienced cruise vacationers are more likely to use discount coupons. Discounting is considered an effective pricing strategy for sustaining long-term profitability. The cruise policy such as passenger tax-free shopping in Hainan
Island, China, is an attempt to fulfill expectations of Chinese tourists with high price sensitivity (Sun et al., 2014). Integrated cruise service products through promoting cooperation among participants in cruise supply chain, including cruise lines, ports and onshore travel agents, serve as a good practice and guideline for the newly developed Chinese market. Chinese passengers may get more convenient cruise service, whereas a win-win situation for all stakeholders would be achieved.

3. Problem description

The cruise package sold in China combines cruise ship tourism and on-shore excursions. Through a pre-determined agreement and/or a contract, a travel agency assists potential cruise passengers directly to create their packages. Figure 1 shows a simplified structural model of the cruise supply chain. This model is the foundation for a two-stage Stackelberg game among the cruise port, cruise line company and travel agency.

The decision-making process is as follows: during the first stage of competition, the cruise port becomes a price leader in the cruise value-added chain. When the cruise company becomes a price follower, according to the market demand, the cruise port formulates the corresponding fees for ship calling at the port. To maximize the cruise port’s own interest, the calling price $p_c$ is decided by the unit variable cost $c$, which is combined with the cruise service cost and reception cost. Once it has the contract with the port, the cruise company then determines the price $p_b$ based on the terminal and facility usage fees $p_c$, the unit variable cost $c_v$ and the fixed cost $c_f$ for operation to maximize profit.

This is one of the unique features in the Chinese cruise market. Compared to the major cruise tourism in the Caribbean and Mediterranean areas where cruise companies have much of
the negotiation power in setting prices and arranging needed long-term contracts with the home ports, cruise in China is considered an additional add-on to the existing port operations. That is because port operations are centrally controlled by the government which determines the amount and type of traffic different from the USA or Europe. Usually with a cruise terminal and other needed facilities, a container port is ready for cruise activities. With limited access currently available for cruise operation, major cruise companies that want to extend their business in China have to work with the ports to receive the exclusive use of the terminal space. In that sense, the dominant role of the game is switching from the cruise line as we typically assume to the port authorities that equip well with needed infrastructure of cruise operation. Thus, the results of a two-stage leader–follower game will be much different if there is another dominant role in the decision-making process.

In the second stage, the competition occurs between the cruise line company and the travel agency. Cruise line company sets up the corresponding tourism product service portfolio based on the market demand. The decision variable, the shipping space underwriting price $p_b$, depends on the unit variable cost $c_v$, which is combined with the cruise service cost and reception cost. The travel agency supplies the cruise tourist resources to the cruise company. The travel agency determines the fare charged to the tourists based on cruise line company’s exclusive sale price $p_a$, and then the cruise line company is responsible for providing the cruise products and services to the tourists.

The structure of the second-stage game, especially the role of the travel agent, is noteworthy when we model the current operation of Chinese cruise market. Compared to the North America and Europe where travellers have a great amount of online information through various of travel booking sites that combine services from airfares, hoteling, local transportation on/off shore excursion, etc., Chinese cruisers must reply on the services of travel agents. There is no direct access for cruise passengers to book and/or arrange itinerary from the online travel sites. Price comparison is within the range between different travel agents for the pre-determined packages but not for travel booking sites.

4. Cruise value chain pricing model
A three-player cruise value chain, including travel agency, cruise line and cruise port, is considered in this paper in a Stackelberg game. Section 4.1 provides the basic model settings, where participants in the cruise value-added chain determine their own prices individually to maximize own profit. In the first stage of the game, the cruise port is a price leader in the chain, and the cruise line company becomes a price follower. In the second stage, the cruise line company is a price leader, followed by the travel agency. After the model setting, we will show profit maximization in the cooperative game to capture the coalition of the entire value-added chain and how the revenues are redistributed back within the chain using Shapley value in Section 4.2.

4.1 Model settings
(1) All parties in the coalition are assumed rational and pursue self-interests.
(2) Prices in the cruise supply chain are:
   • $p_b$: wholesale ticket price underwriting from cruise company $b$ to travel agency $a$;
   • $e_b$: net income per person obtained by cruise company $b$ to provide services such as on/offshore shopping and excursion and gambling at sea;
   • $p_a$: average retail price charged by travel agency;
- $e_a$: net income per person obtained by travel agency $a$ to provide services such as shopping on shore; and
- $p_c$: cost per person due to calling on cruise port $c$.

(3) Costs in the cruise value chain are:
- $c_v$: the unit variable cost regarding the process of cruise navigation;
- $c_f$: the fixed cost in the process of cruise navigation; and
- $c$: the unit cost of cruise port $c$, when the cruise calls on cruise port $c$.

The market demand function is formulated as equation (1):

\[
Q = \alpha - \beta \cdot p_a  
\]  
\[(1)\]

where $\alpha > 0$, $\beta > 0$ and $\alpha$, $\beta$ are constant. $\alpha$ denotes maximized demand of tourists to purchase tickets in the cruise market. $\beta$ denotes the price elasticity of demand, and the price is inversely proportional to the tourists.

In Stage 2, equations (2) and (3) are the profit for the travel agency and cruise company, respectively:

\[
\pi_a = Q \cdot (p_a + e_a - p_b)  
\]  
\[(2)\]

\[
\pi_b = Q \cdot (p_b + e_b - p_c - c_f) - c_f  
\]  
\[(3)\]

According to the first-order condition of equation (2), $\partial \pi_a / \partial p_a = 0$, travel agency sets up pricing strategy according to cruise line’s move, which is shown in equation (4):

\[
\hat{p}_a = \frac{\alpha + \beta (p_b - e_a)}{2\beta}  
\]  
\[(4)\]

In Stage 1, cruise company sets the wholesale price according to the cruise port’s behavior. Combining travel agency’s reaction function [equation (4)] and the first-order condition of cruise company, $\partial \pi_b / \partial p_b = 0$, the pricing mechanism of cruise company are obtained as equation (5):

\[
\hat{p}_b = \frac{\alpha + \beta (e_a - e_b + p_c + c_v)}{2\beta}  
\]  
\[(5)\]

As the price leader in the chain, the cruise port charges service fees to maximize profit [equation (6)]. The pricing strategy of port is shown as equation (7):

\[
\pi_c = Q \cdot (p_c - c)  
\]  
\[(6)\]

\[
\hat{p}_c = \frac{\alpha + \beta (e_a + e_b + c - c_v)}{2\beta}  
\]  
\[(7)\]

Thus, we can obtain the equilibrium prices and total demand as below:
The optimal profit of all participants in the cruise value chain are obtained as equation (10), and the total profit of the cruise chain is the sum of all players [equation (11)]:

\[
\begin{align*}
\pi_a^* &= \frac{(\alpha + \beta \cdot (e_a + e_b - c - c_v))^2}{64 \beta} \\
\pi_b^* &= \frac{(\alpha + \beta \cdot (e_a + e_b - c - c_v))^2}{32 \beta} - c_f \\
\pi_c^* &= \frac{(\alpha + \beta \cdot (e_a + e_b - c - c_v))^2}{16 \beta} \\
\Pi^* &= \frac{7(\alpha + \beta \cdot (e_a + e_b - c - c_v))^2}{64 \beta} - c_f
\end{align*}
\] (10)

4.2 Value chain coordination and profit redistribution

To capture the coalition of the value-added chain with travel agency, cruise company and cruise port in a cooperative way, the profitability of the cruise supply chain is shown in equations (12), and the superscript C represents the cooperation situation:

\[
\Pi^C = Q \cdot (p_a + e_a + e_b - c_v - c) - c_f
\] (12)

According to the first-order and second-order conditions, \( \partial [\Pi^C] / \partial p_a = 0, \partial^2 [\Pi^C] / \partial^2 p_a = -2 \beta < 0 \), we find that the revenue of the cruise value chain is a concave function with the following solution, including optimal retail price [equation (13), optimal market demand [equation (14)] and total revenue of cruise chain [equation (15)]:

\[
p_{a}^{c^*} = \frac{\alpha - \beta (e_a + e_b - c - c_v)}{2 \beta}
\] (13)

\[
Q_{c^*} = \frac{\alpha + \beta (e_a + e_b - c - c_v)}{2}
\] (14)
\[ \Pi^{C^*} = \frac{(\alpha + \beta \cdot (e_a + e_b - c - c_v))^2}{4\beta} - c_f \] (15)

\[ c < p_c < p_a + e_a + e_b - c_v \] (16)

\[ p_c + c_v - e_b < p_a < p_a + e_a \] (17)

When the cruise port determines the pricing strategy within a chain, using conditions obtained in equations (16) and (17), the profit level of the entire chain remains steady. However, the profitability of each participant in the chain will be affected by changes in wholesale and port prices, \( p_b \) and \( p_c \). From equations (8) and (13), we map the optimal solution of pricing and comparing to the results of the two-stage game. Hence, we propose that:

\textit{P1.} Cooperation strategy reduces retail price of cruise service for passengers. At the same time, total revenue of cruise chain is improved.

\textit{Proof.}

Comparing the equilibrium retail price in two scenarios, cooperative scenario and independent decision-making scenario, it could be shown that \( p^*_a > p^{C^*}_a \) [equation (18)]:

\[ p^*_a - p^{C^*}_a = \frac{3\alpha - 3\beta (-e_a - e_b + c + c_v)}{8\beta} > \frac{\beta (p_a + e_a + e_b - c - c_v)}{8\beta} > 0 \] (18)

And then, market demand and cruise chain revenue could also be proved, that is \( Q^* < Q^{C^*} \) and \( \Pi^* < \Pi^{C^*} \).

It will be beneficial for the participants in the chain to adopt the coordination pricing to reduce the quoted price of the whole chain and increase the number of tourists served. Not only does ensuring the service quality of the entire chain, coordination pricing strategy will avoid double counting of the added-value in chain.

However, whether the chain can survive in the long term may depend on how to rationally redistribute profit back to each player participating with the value-added chain. It is a matter of stable cooperation. The Shapley value is commonly used for solving cost allocation, revenue sharing, assignment and partnership dissolution problems according to participants’ contributions to the coalition (Moulin, 1992; Pérez-Castrillo and Wettstein, 2001; Petrosjan and Zaccour, 2003; Macho-Stadler et al., 2007). It has been applied widely to various industries. Examples can be seen by Dubey (1982) for airport with runways catered to different-sized airplanes, Tan and Lie (2002) for cost allocation for users in electric power systems, Narayanam and Narahari (2011) for effective diffusion in social networks and Yu et al. (2014) for carbon emission reduction quotas.

In the field of supply chain, Bartholdi and Kemahlıoğlu-Ziya (2005); Kemahlıoğlu-Ziya and Bartholdi (2011) and Zhang and Liu (2013) demonstrated that Shapley value allocations were guaranteed to motivate participants to respond positively to coordinate in the supply chain. Raghunathan (2003) used Shapley value concept to analyze the expected manufacturer and retailer shares of the surplus generated from information sharing. Rosenthal (2008) developed a model to fairly quantify transactional price in vertically integrated organizations. Results showed that Shapley value allocation was appropriate for perfect information throughout the supply chain. Leng and Parlar (2009) analyzed the
allocation problem of cost savings from sharing demand information among supply chain participants. Gao et al. (2017) proposed the variations of Shapley value as the solution to uncertain coalitional game where players’ payoffs were seen as uncertain variables.

The Shapley value focuses on the research of multi-player cooperation under the profit distribution mechanism, which provides a solution to a cooperative game. $N = \{1, 2, \ldots, n\}$ is called player set, a collection of decision-makers in the cooperation, where $i \in N$ represents the $i$th player. It is supposed that the coalition $S$ is considered any non-vacant set in $N$, and $|S|$ represents the number of players in coalition $S$. To maximize the sum of the apportionment of the union in the game, the members in the union can reach a binding agreement to declare a unified collective action and choose an agreed-upon strategy. We assume that once a union is formed, it will remain stable for the whole process. The grand collection has $N$ members, if $\forall S \subset N$ has a real function $V(S)$, which meets the following two conditions: $V(\emptyset) = 0$ and $V(S_1 \cap S_2) \geq V(S_1) + V(S_2)$, $S_1 \cap S_2 = \emptyset$. Then, $V(S)$ is defined as the characteristic function.

The characteristic function essentially describes the benefit obtained by various cooperation strategies. Benefits of all participants derived from cooperative decision are greater than the sum of participant’s benefit in independent decision-making scenario, which guarantees that it is optimal for all players to participate in cooperation. The vector $X_i(V)$ represents the distribution of total benefits assigned to the $i$th player in a cooperative scenario. The distribution proportions should meet several theorems:

- The potential distribution does not depend upon the sequence of the how players form the coalition.
- The sum of individual benefit is equal to the coalition benefit.
- There is no benefit allocated to the player who has no contribution to the coalition.
- The invariance of the linear transformation.

The distribution results are in line with fairness and equity, according to players’ contribution. Shapley proved that $X_i(V)$ [equation (19)] is the only distribution solution to the cooperation:

$$X_i = \sum_{S \subset S_i} w(|S|) \cdot [V(S) - V(S - \{i\})], \quad i = 1, 2, \ldots, n \quad (19)$$

Where, $|S|$ is the number of coalition includes player $i$, and $w(|S|)$ is the weighting factor, $w(|S|) = \frac{(n - |S|)!}{n!(|S| - 1)!}$.

We adopted the concept of Shapley value to address the excess profit distribution problem among players in cruise value-added chain on the basis of each participant’s contribution.

Table I provides detailed information of all possible coalitions involving cruise port $c$, where let $\zeta = \alpha + \beta (e_a + e_b - c - c_p)$ to simplify expressions.

In Table I, there are four possible coalitions involving cruise port, namely, individual coalition, agency-cruise port coalition, cruise line-port coalition and grand coalition with all players. First, we take the coalition $\{b, c\}$, cruise line and cruise port have formed a coalition without travel agency, as an example to illustrate the computation rules of $V(S)$ for a coalition $S$, which is equal to cooperative profit here. Travel agency who does not join the coalition continue to make pricing decision to maximize self interest in terms of profits, whereas cruise line and cruise port set the price for travel agency to maximize total profits. It is worth mentioning that travel agency and port do not have direct relationship without
cruise line to create a coalition, thus $V(S)$ in the case \{a, c\} is zero. Second, the expected marginal contribution of cruise port to the coalition in each case is the difference of $V(S)$ and $V(S – \{c\})$. Third, a weighted average of cruise port’s marginal contribution is seen as his Shapley value. Thus, the distribution proportion of total benefits to cruise port $c$ is computed as $X_c = \frac{37\xi^2}{384\beta}$.

Similarly, the other two players, cruise lines and travel agency, would also gain extra benefit from involving a stable coalition, which could be, respectively, calculated through Shapley method. The redistribution proportions of cruise line and travel agency are $X_b = \frac{43\xi^2}{384\beta} - c_f$ and $X_a = \frac{\xi^2}{24\beta}$, respectively. Detailed information related to coalitions involving cruise lines and travel agency is shown in Tables AII and AIII in Appendix. Hence, it is proposed that:

**P2.** Cooperative strategy offers the incremental benefit to all participants in the cruise value chain using Shapley redistribution rule once a stable coalition is formed.

**Proof.**

The equilibrium results in two scenarios, independent pricing versus coordinative pricing, are shown in Table II. From P1, we can see the advantages of the cooperative game in terms of the overall performance and revenue. In Table II, the cooperative advantages are further illustrated when we compare the indicators of individual profits versus the coordinative pricing. It is shown that coordinative pricing strategy is the proper strategy for all participants in the cruise value-added chain. Profits within the coalition in the cooperative game are superior to the individual pricing scenario referring to pursuing self-interests. The cooperation among participants in the cruise value chain remains stable because each player benefits from a cooperative way. As for a cruise value chain, a situation of mutual beneficial status of redistribution for travel agency, cruise line and cruise port would be created with Shapley method.

### 5. Built-in incentives policy for cruise

Cruise ports usually adopt specific market strategies and incentives to attract cruise callings and enhance competitiveness, for example, tax rebate on supplies of the

<table>
<thead>
<tr>
<th>$S$</th>
<th>{c}</th>
<th>{a, c}</th>
<th>{b, c}</th>
<th>{a, b, c|</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V(S)$</td>
<td>$\frac{\xi^2}{16\beta}$</td>
<td>0</td>
<td>$\frac{\xi^2}{8\beta} - c_f$</td>
<td>$\frac{\xi^2}{4\beta} - c_f$</td>
</tr>
<tr>
<td>$V(S – {c})$</td>
<td>0</td>
<td>$\frac{\xi^2}{64\beta}$</td>
<td>$\frac{\xi^2}{32\beta} - c_f$</td>
<td>$\frac{\xi^2}{16\beta} - c_f$</td>
</tr>
<tr>
<td>$V(S) - V(S – {c})$</td>
<td>$\frac{\xi^2}{16\beta}$</td>
<td>$\frac{\xi^2}{64\beta}$</td>
<td>$\frac{3\xi^2}{32\beta}$</td>
<td>$\frac{3\xi^2}{16\beta}$</td>
</tr>
<tr>
<td>$</td>
<td>S</td>
<td>$</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$W(</td>
<td>S</td>
<td>)$</td>
<td>1/3</td>
<td>1/6</td>
</tr>
</tbody>
</table>
international cruises and a visa-free policy for the international transit tourists (Department of Transportation, 2014). Not only the policy tools can be creative but also the implementation and initiatives can be seen in different institutional level from the province level to a port-city level. For example, if ports in Hainan are chosen to be the home port for cruises, a certain subsidy is given back to the cruise by voyage (Hainan Province, 2015). Similar subsidy from port to cruise line is observed in the port of Xiamen when it announced in December of 2015 that the maximum subsidy for the cruise company per voyage is approximately $600,000 yuan. Additional incentive is given to the cruise passengers of $150 yuan per person. To support Nansha in planning the cruise development in a three-year timeframe, a total investment of $90m yuan is announced by Guangzhou in December 2016. Furthermore, it rewards new cruise companies to increase the variety of cruise line voyages, and to promote the development of travel agencies in cruise business.

5.1 Analysis of the incentive mechanism
This is done to see the impact of the potential policies or more specifically if those policies can live up with the expectations to align the coordination and the cooperation of the upstream and downstream enterprises in the cruise value chain. Chinese ports are operated in public ownership, thus port authorities adopt subsidy policy on behalf of government authorities. Compared to service suppliers, travel agency and cruise lines, passengers are often identified as the subject for the port authority to give incentives.

When port authority plans to adopt subsidy policy to improve the competitiveness, they could offer incentives to passengers or the service suppliers. Thus, we are going to provide two sciences:

1. incentives to cruise passengers; and
2. incentives to travel agents.

5.1.1 Scenario 1. First, demand side, cruise passengers, is chosen to be the subject of incentives. If a passenger books a cruise package from the travel agency, he/she could
get discount or unit subsidy $\Delta d$ from port authority. Here, superscript $\Delta d$ is used as Scenario 1.

Sequentially, all players in the cruise chain make pricing decision. The cruise port is a price leader, whereas the cruise line becomes a price follower. Then, travel agency sets the retail price according to the wholesale price provided by cruise lines. The sequential decision problem is shown as follows [equations (20)-(22)]:

For the cruise port:

$$P_c : \pi_c^{\Delta d}(p_c) = \max_{p_c \geq 0} \pi_c^{\Delta d}(p_c) \quad (20)$$

For the travel agency:

$$P_b : \pi_b^{\Delta d}(p_b) = \max_{p_b \geq 0} \pi_b^{\Delta d}(p_c^*, p_b) \quad (21)$$

For the cruise line:

$$P_a : \pi_a^{\Delta d}(p_a) = \max_{p_a \geq 0} \pi_a^{\Delta d}(p_b^*, p_a) \quad (22)$$

where the revised profit for all participants in the cruise value chain is shown as equation (23):

$$\begin{align*}
\pi_c^{\Delta d} &= Q \cdot (p_c - c - \Delta d) \\
\pi_b^{\Delta d} &= Q \cdot (p_b + \epsilon_b - p_c^* - c_b) - \epsilon_f \\
\pi_a^{\Delta d} &= Q \cdot (p_a + \epsilon_a - p_b^*)
\end{align*} \quad (23)$$

It is worth mentioning that the market demand function is revised as equation (24) after subsidizing cruise passenger:

$$Q = \alpha - \beta \cdot (p_a - \Delta d) \quad (24)$$

The equilibrium price [equation (25)] is calculated with inverse solution method according to first-order conditions:

<table>
<thead>
<tr>
<th>Independent pricing</th>
<th>Incentives to passengers ($\Delta \text{dollars/person}$)</th>
<th>Incentives to travel agency or cruise company $\Delta \text{dollars/person}$</th>
<th>Cooperative pricing in a coalition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equilibrium service price $p_a$</td>
<td>$8\alpha - \xi$</td>
<td>$8\alpha - \xi + 5\beta \cdot \Delta d$</td>
<td>$8\alpha - \xi$</td>
</tr>
<tr>
<td>Equilibrium market demand $Q$</td>
<td>$8\beta$</td>
<td>$8\beta$</td>
<td>$8\beta$</td>
</tr>
<tr>
<td>Profit for travel agency $\pi_a$</td>
<td>$\frac{\xi^2}{64\beta}$</td>
<td>$\frac{(\xi + 3\beta \cdot \Delta d)^2}{64\beta}$</td>
<td>$\frac{\xi^2}{64\beta}$</td>
</tr>
<tr>
<td>Profit for cruise company $\pi_b$</td>
<td>$\frac{\xi^2 - \epsilon_f}{32\beta - \epsilon_f}$</td>
<td>$\frac{(\xi + 3\beta \cdot \Delta d)^2}{32\beta - \epsilon_f}$</td>
<td>$\frac{\xi^2 - \epsilon_f}{32\beta - \epsilon_f}$</td>
</tr>
<tr>
<td>Profit for cruise port $\pi_c$</td>
<td>$\frac{\xi^2}{16\beta}$</td>
<td>$\frac{(3\beta \cdot \Delta d)^2}{16\beta}$</td>
<td>$\frac{\xi^2}{16\beta}$</td>
</tr>
</tbody>
</table>

Table III. Comparison of subsidy policy and cooperative pricing strategy
The comparison is presented in Table III. Table III Column 3 presents the results. Compared to the incentives to passengers, with independent pricing scenario, it shows that market demand increases, so does service suppliers’ profit. As for the cruise price, passengers save travel cost after internalizing the incentive scheme, although retail service that passengers pay to travel agency is increased by \( \frac{5\Delta d}{c^2} \).

Compared to cooperative pricing strategy, passengers could always gain greater benefit from subsidy policy. However, service suppliers receive lower profit, if the unit subsidy satisfies

\[
\Delta d \in \left( 0, \frac{\sqrt{8\beta} - 1}{3\beta} \right).
\]

This policy to passengers has positive effect only in terms of the market size.

5.1.2 Scenario 2. Table III Column 4 presents the results if service travel agency or cruise lines are chosen as the subject of the incentive. We use travel agent as an example because at the equilibrium state, the effect of port authority subsidy to cruise lines is the same as to the travel agent. If travel agent increases the number of passengers served, he/she could receive rebate \( \Delta s \) per passenger from the port authority. Here, superscript \( \Delta s \) is used as Scenario 2.

The sequential decision problem is shown as follows [equations (26)-28]:

\[
P_c : \pi^*_c(p_c) = \max_{p_c \geq 0} Q \cdot (p_c - c - \Delta s)
\]

\[
P_b : \pi^*_b(p_b) = \max_{p_b \geq 0} Q \cdot (p_b + e_b - \hat{p}_c - c_v) - c_f
\]

\[
P_a : \pi^*_a(p_a) = \max_{p_a \geq 0} Q \cdot (p_a + e_a - \hat{p}_b + \Delta s)
\]

The equilibrium price [equation (29)] is calculated according to the first-order conditions in equation (29):

\[
P_c^{\Delta s} = \frac{\alpha + \beta \cdot (e_a + e_b + c - c_v + 2\Delta s)}{2\beta}
\]

\[
P_b^{\Delta s} = \frac{3\alpha + \beta \cdot (3e_a - e_b + c + c_v + 4\Delta s)}{4\beta}
\]

\[
P_a^{\Delta s} = \frac{7\alpha + \beta \cdot (-e_a - e_b + c + c_v)}{8\beta}
\]

It can be seen that the retail service price \( p_a^{\Delta s} \) in this subsidy situation is equal to independent pricing scenario, so the market demand is also the same. Related solving
results, including market demand and individual profit, are shown in the fourth columns of Table III. It is ineffective for cruise port to improve comparative advantage with subsidy policy to cruise lines when port authority goes after individual profit maximizing. It is proposed that:

\[ P3. \text{ Compared to the cooperative pricing strategy, incentive mechanism works only if } \Delta d > \left( \frac{\sqrt{\beta} - 1}{3\beta} \right) \xi \text{ holds, implying that self-interest of each participant is dominated by the greater good from the coalition. Among two industry practices, rebate or discount to passengers is considered more effective than direct subsidy to cruise line and/or travel agency. The latter creates less impacts toward both market share and total profit.} \]

Proof. The optimal results under various scenarios are shown in Table III. Compared with the results of cooperative pricing strategy, both travel agency and cruise company could derive extra benefit from subsidy offered to passengers under the condition of \( \pi_a^{\Delta d} > \pi_a^* \) and \( \pi_b^{\Delta d} > \pi_b^* \).

6. Conclusions
The increasing importance of coordination, cooperation and vertical integration may effectively impact performance for cruise lines, cruise ports and involved service providers. This paper studies the profit distribution from the perspective of the vertical integration of cruise product pricing in the cruise supply chain. The model can further be used to examine in what circumstance the integration and/or coordination live up with the expectation to improve performance for all involved parties. To realize long-term win-win situation and continuously sustainable operations in the cruise supply chain, we adopt independent pricing and cooperative pricing models to study the profitability of the cruise supply chain, including travel agency, cruise company and cruise port. The following conclusions are drawn from the research:

- In the cruise value-added chain, participants of cruises chain can set price independently or adopt pricing strategy in cooperation. Compared with independent pricing, the equilibrium retail prices from cooperative pricing cost less to cruise passengers. It implies that the social benefit is greater. Meanwhile, total revenue of cruise chain is improved in cooperative pricing strategy.
- To avoid the instability of the operation of the entire chain, the Shapley method is used for revenue redistribution. We conclude that cruise service suppliers, cruise line company and travel agency receive higher profit under the cooperative coalition model than independent pricing strategy focusing on individual self-interest.
- This paper evaluates the effects of cruise subsidy policy, including a quantitative analysis of the marketing effect while different members are selected as the subject of the subsidies. Comparing two subsidy scenarios, when passengers are given incentives, policy creates positive effects to improve cruise market size and to increase profit of individual participants in the chain. However, subsidy policy is not as effective as cooperative pricing strategy, if insufficient incentives are provided.

Further discussion regarding applying the game theory model can be done in multiple ways. First, a detailed value chain empirical analysis including survey of reposition timeline and schedule, operating contracts with the participants in the value-added chain, resupply cost breakdowns and revenue streams, etc. will provide more insights.
### Table IV.
Cruise port schedule for Shanghai

<table>
<thead>
<tr>
<th>Date</th>
<th>Vessel</th>
<th>Cruise line</th>
<th>Arrival-Departure</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>3 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
<tr>
<td>4 March, 2018</td>
<td>Amadea</td>
<td>Phoenix Reisen</td>
<td>12:00-20:00</td>
</tr>
<tr>
<td>5 March, 2018</td>
<td>Oceania Nautica</td>
<td>Oceania Cruises</td>
<td>n/a</td>
</tr>
<tr>
<td>6 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>7 March, 2018</td>
<td>Oceania Nautica</td>
<td>Oceania Cruises</td>
<td>n/a</td>
</tr>
<tr>
<td>7 March, 2018</td>
<td>Viking Sun</td>
<td>Viking Ocean Cruises</td>
<td>n/a</td>
</tr>
<tr>
<td>8 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
<tr>
<td>9 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>10 March, 2018</td>
<td>P&amp;O Arcadia</td>
<td>P&amp;O Cruises</td>
<td>n/a</td>
</tr>
<tr>
<td>12 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
<tr>
<td>13 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>15 March, 2018</td>
<td>Columbus</td>
<td>Cruise and Maritime</td>
<td>12:00-20:00</td>
</tr>
<tr>
<td>17 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
<tr>
<td>18 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>22 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
<tr>
<td>23 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>24 March, 2018</td>
<td>Norwegian Jewel</td>
<td>NCL</td>
<td>07:00-19:00</td>
</tr>
<tr>
<td>25 March, 2018</td>
<td>Majestic Princess</td>
<td>Princess Cruises</td>
<td>07:00-19:00</td>
</tr>
<tr>
<td>25 March, 2018</td>
<td>Star Legend</td>
<td>Windstar Cruises</td>
<td>10:00</td>
</tr>
<tr>
<td>26 March, 2018</td>
<td>Queen Elizabeth</td>
<td>Cunard Line</td>
<td>n/a</td>
</tr>
<tr>
<td>26 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
<tr>
<td>27 March, 2018</td>
<td>ms Volendam</td>
<td>HAL</td>
<td>n/a</td>
</tr>
<tr>
<td>27 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>28 March, 2018</td>
<td>ms Volendam</td>
<td>HAL</td>
<td>n/a</td>
</tr>
<tr>
<td>29 March, 2018</td>
<td>ms Volendam</td>
<td>HAL</td>
<td>n/a</td>
</tr>
<tr>
<td>31 March, 2018</td>
<td>Norwegian Joy</td>
<td>NCL</td>
<td>06:00-16:00</td>
</tr>
<tr>
<td>31 March, 2018</td>
<td>Oceania Insignia</td>
<td>Oceania Cruises</td>
<td>08:00</td>
</tr>
<tr>
<td>31 March, 2018</td>
<td>Quantum of The Seas</td>
<td>Royal Caribbean</td>
<td>07:00-16:45</td>
</tr>
</tbody>
</table>

**Source:** crew-center.com

### Table V.
Cruise port schedule for Dalian

<table>
<thead>
<tr>
<th>Date</th>
<th>Vessel</th>
<th>Arrival-Departure</th>
</tr>
</thead>
<tbody>
<tr>
<td>01 April, 2018</td>
<td>Star Legend</td>
<td>13:00-22:00</td>
</tr>
<tr>
<td>09 May, 2018</td>
<td>Seabourn Sojourn</td>
<td>10:00-20:00</td>
</tr>
<tr>
<td>19 October, 2018</td>
<td>Viking Spirit</td>
<td>n/a</td>
</tr>
<tr>
<td>16 November, 2018</td>
<td>Viking Spirit</td>
<td>n/a</td>
</tr>
</tbody>
</table>

**Source:** crew-center.com
towards the governing purposes. Meanwhile, the information gathered through the survey can be used toward the parameter setting to verify the cooperative game model obtained in this research.

We revisited the cruise port schedule for the major cruise home ports in China such as Shanghai, Sanya, Tianjin, Dalian, Qingdao and Xiamen to provide a case-based sensitivity analysis. This approach will assess the critical issues such as port investment with the involvements of private sectors, port congestion with the possible internal conflicts with the terminal utilization, and an important aspect such as the implications of further port subsidy policy. For example, when comparing the cruise port schedule of Shanghai in Table IV with the regional port in Dalian in Table V, the former is more likely to have issue of congestion and internal competition of space, whereas the later may need to focus on the marketing and subsidy strategies to make the port cruise-friendly. Not only the call schedule, to maximize the regional economic impacts generated by the cruise activities, itinerary and travel packages offered by the travel agents, but also incentives toward the cruise companies can be examined.

References


Department of Transportation (2014), available at: www.gov.cn/gongbao/content/2014/content_2711449.htm


### Appendix

Table AI provides the distributed benefit of cruise company \(b\) in the cruise value chain based on the Shapley method. This is the case most likely to show the features of the US cruise markets and the market in the Mediterranean Sea when cruise company is the one that dominates the chain with proper alignment of up/downstream service providers.

According to Table AI, the distributed benefit of Cruise Company \(b\) in the cruise supply chain is:

\[
X_b = \frac{43\zeta^2}{384\beta} - c_f, \quad \zeta = \alpha + \beta (e_a + e_b - c - c_v)
\]

Table AII provides the distributed benefit of Travel Agency \(a\) in the cruise value chain based on the Shapley method.

Here, we use the concept of Shapley value to address the excess profit distribution problem among players in cruise value added chain on the basis of each participant’s contribution. According to Table I, the distributed benefit of Travel Agency \(a\) in the cruise supply chain is as below:

\[
X_a = \frac{\zeta^2}{24\beta}, \quad \zeta = \alpha + \beta (e_a + e_b - c - c_v)
\]
Table AI.
Profit distribution of Cruise Company b

<table>
<thead>
<tr>
<th>S</th>
<th>{b}</th>
<th>{a, b}</th>
<th>{b, c}</th>
<th>{a, b, c}</th>
</tr>
</thead>
<tbody>
<tr>
<td>V(S)</td>
<td>$\frac{\xi^2}{32\beta} - c_j$</td>
<td>$\frac{\xi^2}{16\beta} - c_j$</td>
<td>$\frac{\xi^2}{8\beta} - c_j$</td>
<td>$\frac{\xi^2}{4\beta} - c_j$</td>
</tr>
<tr>
<td>V(S - {b})</td>
<td>0</td>
<td>$\frac{\xi^2}{16\beta}$</td>
<td>$\frac{\xi^2}{8\beta}$</td>
<td>0</td>
</tr>
<tr>
<td>V(S - V(S - {b}))</td>
<td>$\frac{\xi^2}{32\beta} - c_j$</td>
<td>$\frac{3\xi^2}{64\beta} - c_j$</td>
<td>$\frac{\xi^2}{16\beta} - c_j$</td>
<td>$\frac{\xi^2}{4\beta} - c_j$</td>
</tr>
</tbody>
</table>

| | S | | | | |
| | W(|S|) | 1/3 | 1/6 | 1/6 | 1/3 |

Table AII.
Profit distribution of participants in the value chain

<table>
<thead>
<tr>
<th>S</th>
<th>{a}</th>
<th>{a, b}</th>
<th>{a, c}</th>
<th>{a, b, c}</th>
</tr>
</thead>
<tbody>
<tr>
<td>V(S)</td>
<td>$\frac{\xi^2}{64\beta}$</td>
<td>$\frac{\xi^2}{16\beta} - c_j$</td>
<td>0</td>
<td>$\frac{\xi^2}{4\beta} - c_j$</td>
</tr>
<tr>
<td>V(S - {a})</td>
<td>0</td>
<td>$\frac{\xi^2}{32\beta} - c_j$</td>
<td>$\frac{\xi^2}{16\beta}$</td>
<td>$\frac{\xi^2}{8\beta} - c_j$</td>
</tr>
<tr>
<td>V(S - V(S - {a}))</td>
<td>$\frac{\xi^2}{64\beta}$</td>
<td>$\frac{\xi^2}{32\beta}$</td>
<td>$\frac{\xi^2}{16\beta}$</td>
<td>$\frac{\xi^2}{8\beta}$</td>
</tr>
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| | S | | | | |
| | W(|S|) | 1/3 | 1/6 | 1/6 | 1/3 |

Corresponding author
Grace W.Y. Wang can be contacted at: wangw@tamug.edu
Competitive intensity and inefficiency in European container ports
An empirical investigation using SFA
Axel Merkel
Faculty of Logistics, Molde University College, Molde, Norway

Abstract
Purpose – The purpose of this paper is to empirically examine the relationship between intensity of competition and technical efficiency of large European container ports, accounting for regional diversities and spatial aspects of inter-port competition.

Design/methodology/approach – The analysis consists of applying a stochastic production frontier approach to a dataset of 77 large European container ports over the period 2002-2012, with inefficiency terms simultaneously modeled as a function of (among other factors) a constructed index of competitive intensity at different spatial levels.

Findings – The results indicate that there is no significant negative effect of competitive intensity on efficiency. In fact, for competing European ports within a proximity of 300 km, a higher level of competition is found to be associated with a higher level of technical efficiency.

Originality/value – The originality of the paper stems from its particular focus on European port regions and its novel findings in this context, which have implications for the discussions regarding pro-competitive port policy and regulation in the European Union.

Keywords Stochastic frontier analysis, Inter-port competition, Port policy

Paper type Research paper

1. Introduction
Over the past two decades, development of a common policy framework regulating the governance of major European seaports has been in progress. Simultaneously, several governments of European Union member states have implemented own institutional reforms in their port sectors (Chlmoudis and Pallis, 2005; Baird and Valentine, 2007; Pallis and Syriopoulos, 2007; Valleri et al., 2006). A recurring objective of proposed common port policies has been to increase the autonomy and transparency of port finances, imposing stricter control on national subsidization to achieve greater competitive pressure between ports. In drafting the principles of a uniform port policy, the European Parliament stated that overcapacity has been a problem for the European container port sector, recognizing also that competitive investment, i.e. a “spiraling” effect of ports competing with infrastructure size to attract and accommodate a fleet of continuingly expanding vessels, was a potential cause of this overcapacity (European Parliament, 1999). Such concerns cannot be seen as unfounded, as various studies have pointed out that higher competition in container port service production is a potential inducer of excess capacity (Haralambides, 2002; Haralambides et al., 2002). At the same time, there is an obvious role for competition in
promoting and producing efficient outcomes through the deterrence of monopolistic pricing and related practices, which is similarly emphasized by seminal work on the subject (Goss, 1990).

Increasing the autonomy of important European seaports and harmonizing differences in the institutional governance between member states to create a more competitive environment could have a significant impact on the efficiency of the European maritime and multimodal transport system. There is a wide array of existing research related to applying efficiency measurement and benchmarking methods to seaports (Tongzon and Heng, 2005; Cullinane and Song, 2006; Trujillo and Tovar, 2007). However, the explicit relationship between intensity of competition between ports and estimated efficiency has been the subject of only two published studies, none of which pertain to the European market specifically. Using an international sample of 200 container ports, De Oliveira and Cariou (2015) applied a data envelopment analysis (DEA) framework to study how the intensity of competition within different degrees of proximity from each port explained efficiency estimates. Their findings indicate that within a radius of 400-800 km, efficiency decreases with increasing competitive intensity, yielding support for the hypothesis that regional competition between ports may induce excessive investment. On the other hand, Yuen et al. (2013) found that competitive intensity, both within and between Chinese ports, is positively related to DEA estimates of technical efficiency. The published evidence as to whether inter-port competition may cause inefficiency is thus mixed, making it a relevant topic to pursue. Even though there have been long-running attempts to promote increased competition through Union policy (Chlomoudis and Pallis, 2002), existing studies of port efficiency in European countries using stochastic frontier analysis (SFA) or DEA (Barros and Athanassiou, 2004; Barros, 2006; Coto-Millan et al., 2000; Cullinane and Wang, 2006; Cullinane and Song, 2006; Trujillo and Tovar, 2007; Martinez-Budria et al., 1999; Rodrigues-Alvarez and Tovar, 2012) do not account for competitive intensity as a factor influencing the performance of port service production. The contribution of this study is therefore an empirical test of the hypothesis that increased competition between European ports induces inefficiency through excessive investment. If it is the case that a high level of competition between ports tends to cause overcapacity, we should expect to find that intensity of competition has a significantly negative impact on efficiency. To account for differences in governance structures and policy, five major port regions with diverse institutional features are compared. Using European ports as objects of analysis is valuable because it can potentially yield findings relevant to the development and desirable direction for a harmonized policy framework.

This paper is structured in the following way. In Section 2, previous research regarding port policy, competition and efficiency is reviewed. In Section 3, the methodology for analyzing the relationship between competition and efficiency is outlined. In Section 4, the data are introduced and empirical models are specified. In Section 5, the results of estimation are presented. Section 6 is devoted to a short discussion regarding possible implications for port policy, and Section 7 summarizes the conclusions drawn from the study.

2. Background and theoretical aspects

2.1 Port competition and policy in Europe

Issues of port governance, such as determination of user charges, degree of public subsidization, financial autonomy and economic objectives, lie at the heart of the study of
seaports in economics. The European port system has historically comprised fragmented aspects of policy in this area, but there have been notable developments toward policy harmonization. An important example is the “framework for the provision of port services and common rules on the financial transparency of ports” (European Union, 2017a, 2017b). This constitutes a regulatory framework, which mandates among other things that the direct or indirect receipt of public funds in ports has to be transparently disclosed. The provision applies from 2019 and will concern the 329 ports included in the trans-European transport network (TEN-T).

Surveying the historical development, it is clear that there have been expressed intentions by European policymakers to harmonize institutional factors in a common “European Ports Policy” for several decades. Among the objectives of such a policy, as stated by the European Parliament (1993), would be to promote free and fair competition among ports. The European Parliament advocated controlling subsidies to ports by limiting direct national governmental support, while also increasing the transparency of port accounts (Chlmoudis and Pallis, 2002). Facilitating controlled financial flows to European ports that are considered essential to the transport system was intended to level the playing field and lead to more competition between ports. While the proposed policy plan was not executed, it was updated in a follow-up report (European Parliament, 1999), where structural changes in the port industry such as liberalization of port operations from public control and technology changes in shipping were addressed. The report also addressed overcapacity because of large infrastructure investments, citing figures estimating the overcapacity in the North Sea and Mediterranean to be at 52 per cent and 35 per cent, respectively, while also acknowledging that this might be caused by competitive behavior. Overcapacity was in this context defined as the “the positive difference between the capacity of the port and the existing traffic” (European Parliament, 1999). It is not fully clear how the capacity, i.e. the maximum achievable amount of throughput, was found. It is worth noting that overcapacity is a complicated term, which suggests that capacity exceeds a certain level that is considered sufficient. However, it is easily shown that some degree of excess capacity in ports is both common and arguably rational due to the time it takes to expand capacity and the volatile nature of demand. As a spike in demand can only be met by an increased capacity utilization rate in the short run, “excess capacity” may be a necessary measure to mitigate bottlenecks or congestion problems. Following a subsequent series of reports and policy proposals (Chlmoudis and Pallis, 2005, for an extensive review), the diversity of the industry and the heterogeneous institutional structures of member states posed as a barrier toward the implementation of a common policy. However, the above-mentioned provision aimed to give European ports more autonomy in setting infrastructure charges while also increasing the transparency of public funding was ratified by the European Parliament in 2016 (European Union, 2017b).

An argument for increasing the autonomy of port authorities is that this would allow them to be flexible in responding to changes in the transport sector, while also relieving administrative burden on central governments (European Parliament, 1999). In addition, high levels of autonomy may spur rivalries between ports, which could incentivize efficiency improvements. An argument against increased autonomy is that a lack of a centralized authority yields duplication of efforts: excessive capacity expansions, aiming to secure local economic benefits could be undertaken in too many areas. A potential downside of a high level of port autonomy is inefficiency because of competitive over-investment. This is not a new issue. In fact, Jansson and Shneerson (1982) showed that using an approach based on queueing theory that under optimal pricing and investment principles, a fully decentralized system of ports (each port decides with complete autonomy its capacity) and a fully centralized system of ports (capacity is allocated to all ports by a central planner) yield identical and efficient
outcomes. Optimal investment and pricing principles are however unlikely to be applied in practice. In empirical work, port pricing is seldom found to bear any relation to the notion of social efficiency (Meersman et al., 2014) and port investment under competition is subject to a variety of complicating factors. Musso et al. (2006) distinguish between four categories of economic impact that arise from port investments, namely, financial returns to investors, microeconomic benefits in the form of reduced generalized cost of using the port, local effects on employment (as well as possible multiplier effects) and negative effects in terms of environmental externalities. The local public ownership structure of ports in most of northern Europe means that port investment may act as an instrument for regional competition for local macroeconomic benefits. In multi-country port regions, public authorities’ attempt to strengthen the competitive position of nationally important ports could induce a higher degree of competition between ports (Verhoeff, 1981). From the standpoint of the individual country or region, economic benefits in the form of attracting/retaining jobs and industrial activity may be seen as justifiable motives for large port infrastructure investments. From the perspective of the European Union, however, such benefits may rather be seen as being diverted from elsewhere within Europe, while at the same time potentially exacerbating overcapacity. This can be seen as an important factor for levying controls on national subsidization of ports.

2.2 Regional divisions in European port governance
Port governance is a multifaceted concept, which can be analyzed with respect to a variety of parameters. Verhoeven and Vanoutrive (2012) identify seven such parameters: devolution, corporate governance, operational profile, functional autonomy, functional pro-activeness, investment responsibility and financial autonomy. While there has been development toward integration, the European port industry has until now eluded a common policy framework. Institutional differences in port governance are prevalent and the variation is largely regional (Suykens and Van de Voorde, 1998; Chlmoudis and Pallis, 2002; Verhoeven, 2011; Verhoeven and Vanoutrive, 2012). Verhoeven (2011) identifies in a comprehensive survey of European ports’ governance structures three large and distinct styles of governance: Hanse, Latin and Anglo–Saxon. The Hanse style of governance applies to northern continental Europe and Scandinavia and is distinguished by local municipal autonomy in port governance. The Latin category comprises southern European countries on the Mediterranean and Atlantic coast (France, Portugal, Spain, Italy and Greece) and is characterized by a more centralized public governance structure. Finally, the Anglo–Saxon category consists of the UK and Ireland and is distinguished by independence and financial autonomy with little public intervention.

Regional divisions of the European port system are made in different ways in the literature. Chlmoudis and Pallis (2002) identify four distinct regions: the Baltic Sea region, the North Sea region (including the UK), the Atlantic region and the Mediterranean Sea region. This is similar to the regional distinction found in Notteboom (2009), which divides the European container port system into Hamburg-Le Havre, Mediterranean, UK (including Ireland), Atlantic, Baltic and Black Sea regions.

2.3 Port competition and operational efficiency
Efficiency in port operations could informally be defined as the ability with which a port produces its core services given its current input factors. A port that is efficient, relative to some benchmark, will have a low level of slack capacity, meaning that inputs to the production of port services are not idle to a large degree. The empirical measurement of port efficiency using benchmarking techniques have been applied with varied purposes. These range from estimating effects of policy reform and regulation (Estache et al., 2002; Gonzáles and Trujillo 2008, Chang et al., 2018) to studying differences in ownership structure (Cullinane et al., 2002;
This wide array of existing port efficiency literature shows that there are numerous methods available for studying the relationship between competitive intensity and performance. There is also a large body of research dedicated to studying inter-port competition, ranging from early studies such as Verhoeff (1981) and Slack (1985) to more recent work such as Wang et al. (2012) and Homosombat et al. (2016). A notable portion of this work has treated port competition from a game-theoretic standpoint, studying strategic aspects of investment levels (Anderson et al., 2008) and pricing competition (Ishii et al., 2013). The notion that competition between autonomous ports can spur improvements in efficiency is somewhat complicated. Port investments are subject to a significant time lag between initialization and completion, and they are largely of a “sunk cost” nature, meaning that it is difficult to divest in port capacity (Musso et al., 2006). Being of an irreversible nature, such investments may be subject to what Abel and Eberly (1999) term the “hangover effect”, meaning that firms typically find themselves with large capital stocks because they cannot sell capital even when it has a low marginal revenue product. Not all assets in ports are irreversible investments. For instance, while investing in a wide and deep approach channel is permanent, cargo-handling equipment may be sold to another goods handler. However, once a sunk investment in a particular factor of production is made, other factor inputs may become more productive, reducing incentives for divestment of sellable capital units or even stimulating further investment. If ports subject to more intense competition tend to invest in capacity to a larger degree, we should therefore expect to see a greater level of capacity in competitive port regions. Barring a counteracting improvement of efficiency because of competitive pressure, increased competition between ports could be expected to lead to reduced efficiency.

While the efficiency of seaports has been studied extensively, few such studies attempt to incorporate competition as an element potentially affecting performance. One study that does analyze the impact of competition on efficiency finds that estimated port efficiency decreases with the intensity of regional competition (De Oliveira and Cariou, 2015). Another study (Yuen, et al., 2013) finds that the efficiency of container terminals is positively correlated with the level of inter-port competition. Conceptually, this study follows that of De Oliveira and Cariou (2015), but with some key differences. First, while their study has global coverage, this study is applied to the European container port sector in particular. If port policy interacts with competition and efficiency, this motivates the study of specific regions to develop and further the literature on European port policy and governance. Second, while their study applies a non-parametric approach to determining efficiency, this study uses an econometric framework. Though this approach requires potentially restricting assumptions of a functional form and error term distribution, it has advantages in that it can accommodate random noise in the data in a straightforward way (Coelli et al., 2005). Another advantage with the parametric approach applied is that efficiency frontier estimation and analysis of inefficiency determinants can be accommodated in a one-step procedure. This will be elaborated upon in the Methodology section.

3. Methodology
The aim of efficiency analysis is to measure the extent to which a firm or some other decision-making unit (DMU) achieves a maximum level of output given a set of inputs, combined in an optimal way (Farrell, 1957). The measurement of efficiency is based on an estimated distance between the firm’s actual level of production and an efficient frontier of maximum achievable production for given sets of inputs. Empirical analysis of efficiency requires some method of estimating this benchmark frontier. The two dominating methods
are DEA and SFA (Lovell, 1993). The former is a non-parametric linear programming approach that has the advantage that it does not require any presupposition of the firm’s production technology (Charnes et al., 1978). As a drawback, non-parametric methods complicate statistical testing of hypotheses, a problem which can be solved using a stochastic approach. In stochastic frontier analysis, a cost or production function is estimated with a two-part composite error term. One part is an inefficiency effect indicating distance from the frontier, and the other part is some well-behaved noise term (commonly assumed to be normally distributed) (Meeusen and van den Broeck, 1977; Aigner et al., 1977). In SFA, choice of functional form is crucial. In empirical applications, the chosen approaches are often that of the simple Cobb–Douglas, which restricts the returns to scale in production to be a constant (not to be confused with returns to scale being constant) or the generalized translog form, which adds cross-product terms for each input and does not restrict substitution elasticities to be unity (Coelli et al., 2005). For the N-input, single output case, the Cobb–Douglas function is:

\[ Y_i = \beta_0 \prod_{n=1}^{N} \beta_n x_{ni} \]  

(1)

And the translog function is:

\[ Y_i = \exp \left[ \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{ni} + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{nm} \ln x_{ni} \ln x_{mj} \right] \]  

(2)

The Cobb–Douglas and translog functional forms are, respectively, first- and second-order approximations of an unknown relationship. The latter could generally be said to be more attractive, as the more flexible form reduces the amount of potentially restrictive assumptions required in specifying the function to be estimated. In practice, the advantage of the translog over the Cobb–Douglas form can be assessed through a likelihood-ratio (LR) test (Wooldridge, 2010). Once estimated, the functions allow for tests of other statistical hypotheses. Of particular interest in assessing industry regulation and policy is testing whether the production of container port services exhibits constant returns to scale (CRS). In the Cobb–Douglas model, the assumption of CRS can be tested by imposing the restriction that the sum of output elasticities is equal to one, i.e.:

\[ \{ \beta_1 + \beta_2 + \beta_3 + \beta_4 = 1 \} \]

(3)

where, \( \beta' = (\beta_1, \beta_2, \beta_3, \beta_4) \) are Cobb–Douglas parameters in a four-input model. The four-input example is convenient to use here, as it directly applies to the subsequent empirical analysis. For the translog model, the CRS assumption can be tested by imposing the restriction that the sum of output elasticities is equal to one, i.e.:

\[
\begin{cases}
\beta_1 + \beta_2 + \beta_3 + \beta_4 = 1 \\
\beta_{11} + \beta_{12} + \beta_{13} + \beta_{14} = 0 \\
\beta_{12} + \beta_{22} + \beta_{23} + \beta_{24} = 0 \\
\beta_{13} + \beta_{23} + \beta_{33} + \beta_{34} = 0 \\
\beta_{14} + \beta_{24} + \beta_{34} + \beta_{44} = 0
\end{cases}
\]  

(4)
The validity of these restrictions can be tested using the Wald test principle (Wooldridge, 2010). In the previous literature dedicated to estimating seaport efficiency, both DEA (Martinez-Budria et al., 1999; Cullinane and Wang, 2006; Barros, 2006) and SFA (Liu, 1995, Coto-Millan et al., 2000; Trujillo and Tovar, 2007; Estache et al., 2002) approaches have been used. Among the SFA applications, functional form is usually decided by estimating both a Cobb–Douglas and translog variant and assessing whether the more restrictive Cobb–Douglas is adequate through a LR test. The Cobb–Douglas form is in some cases found to be sufficient (Trujillo and Tovar, 2007; Tongzon and Heng, 2005), while in other cases the translog form is found to be superior (Coto-Millan et al., 2000; Estache et al., 2002). The rationale for choosing Cobb–Douglas and translog functional forms in this study is that they provide, respectively, a parsimonious and flexible model. The choice of model is ultimately determined by a LR test. As the production function variables in this dataset (to be introduced) do not include zeroes, there is also no issue of constructing logarithms.

In many applications of efficiency analysis, the purpose is to investigate the determinants of inefficiency, i.e. to explain why some DMUs do not perform as well as their studied counterparts. In DEA applications, it is common to use a two-step approach, such as that proposed by Simar and Wilson (2007). This approach takes into account the potentially complex serial dependence and truncation that characterizes DEA estimates of efficiency. Two-step methods that involve first estimating the efficiency of units, and then regressing these on explanatory factors have also been proposed for SFA (Pitt and Lee, 1981). An arguably better approach is to account for the inefficiency determinants directly in the estimation of the production frontier (Kumbhakar et al., 1991; Battese and Coelli, 1995). In fact, Wang and Schmidt (2002) show in a simulation study that for SFA, the two-step approach for explaining inefficiency leads to significant bias, favoring the one-step approach. The one-step approach can be described by first assuming for the (log-linearized) production function:

\[
\ln Y_{it} = \beta_0 + \beta_1 \ln X_{1, it} + \ldots + \beta_k \ln X_{k, it} + v_{it} - u_{it}
\]

(5)

where, \( k \) is the number of entered factors of production (X), that \( u \) is a non-negative inefficiency term composed by:

\[
u_{it} = \alpha_0 + \alpha_1 Z_{1, it} + \ldots + \alpha_l Z_{l, it} + W_{it}.
\]

(6)

In the latter equation, \( u \) is assumed to depend on a set of \( l \) factors (Z) which characterize the production environment of port \( i \) at time \( t \). The distribution of the inefficiency term is assumed to be:

\[
u_{it} \sim i.i.d. N^+ \left( \alpha Z, W, \sigma_u^2 \right)
\]

(7)

where, \( W \) is a normally distributed random variable, truncated at \((-\alpha Z)\). Using the above described estimation framework, it is possible to specify hypothesized determinants of inefficiency as variables in \( Z \). The main effect of interest in this study is that of competitive intensity. To account for other factors that have been shown to influence inefficiency, variables from previous studies are also incorporated.

In assessing the impact of port competition on estimated efficiency, previous proxies for competition have included distance to nearest port (Yuen et al., 2013, Merkel and Holmgren, 2017) and a Herfindahl–Hirschman index (HHI) of market concentration (De Oliveira and Cariou, 2015). The advantage of the market concentration index over the more simplistic
4. Empirical production functions and data

This study takes a production function approach to deriving estimates of technical efficiency of seaports. Before arriving at an estimable function, a few conceptual features of port services should be noted. Jansson and Shneerson (1982) note that port services are (as all services) non-storable. This implies that production and consumption need to occur simultaneously. From this obvious reasoning, two general statements can be made:

1. In some theoretically complete model of port service production, the time and effort provided by the user of services should be accounted for as inputs to production.

2. There may exist significant substitution between producer and user inputs. A lack of modern handling equipment on part of the port or terminal will inevitably require an increased amount of user time, while a greater level of capital inputs will enable less time usage on part of the consumer. This is analogous to the statement that a high (low) level of capacity utilization yields a low (high) cost of capacity and high (low) expected total waiting times.

While the points made above imply that the user side of port services should be included in a complete production function, data availability is a hindrance. Turnaround times in port are theoretically observable, but there are large difficulties in gathering and harmonizing such data with the historical record of port assets and aggregated throughput levels (not least in studies with many DMUs). In some studies (Akinremi, 2016), waiting time is included as a factor of production, but in most studies it is not (for a review of this issue, see Merkel and Holmgren, 2017). Noting that omission of user inputs is a second-best solution does however at least allow one to keep in mind that what is being estimated is technical efficiency with regard only to producer inputs. This has important implications and certain limitations for the interpretation of results and findings.

This study considers four inputs to the production of container throughput (TP), measured as annual number of 20-foot-equivalent container units (TEUs) handled. The inputs are total terminal area (TA) in square meters, total berth length (BL) in meters, total number of quay cranes and reach stackers/front end handlers with a carrying capacity of at least 25 tons (NC) and maximum allowed depth of the deepest berth in the port (MD) in meters. Terminal area and berth length both correspond to a port’s endowment of land, while the number of cargo handling machinery units correspond to capital. Depth can be considered a semi-natural resource; ports situated on natural harbor sites are well suited to accommodate deep-draft ships. It is semi-natural in the sense that existing facilities can be augmented through dredging operations. Because of the trend of increasing container ship sizes during the period of study, draft has become a bottleneck for ports, and is therefore assumed to reflect a source of competitive advantage. As in a large number of similar analyses of port efficiency, labor does not enter the estimated production function. The reason for having to ignore labor inputs is scarcity of data, as well as a lack of data consistency, in cross-country samples. However, it has been argued (So et al., 2007; Cullinane et al., 2002; Tongzon and Heng, 2005; Serebrisky et al., 2016) that labor occurs in more or less
fixed proportion to capital inputs. If this should be the case, it means that variation in the use of labor as a factor of production is contained in the variation of capital inputs. This assumption, stated explicitly, is that the operating labor requirements for the capital equipment units measured in this study are the same across large European container ports.

For a total of 77 ports and six biennial years of observation, data for input factors was gathered from Containerisation International Yearbook (2002, 2004, 2006, 2008, 2010, 2012), and throughput data for the same years was retrieved from the Eurostat (2016b) database. The use of biennial years of observation is necessitated by the fact that for the ports in the sample, infrastructure variables are unavailable or missing for several years. As a criterion for inclusion, ports with an average annual throughput lower than 10,000 TEUs during the period 2002-2012 were excluded. The reason for applying such a criterion is to ensure a higher level of data consistency and because of the assumption that very small ports do not have a large effect on the competitive intensity of port regions. In total, data collection yielded a panel dataset of 462 observations. The ports included for analysis can be divided into five regions: the Mediterranean, the Atlantic, the UK, Scandinavia/Baltic and Hamburg-Le Havre. Out of the sample of 77 ports, 57 are classified as “core” parts of the trans-European transport network and the other 20 are classified as “comprehensive” (European Union, 2017a). The variables entered as factors of production are summarized in Table I and the development in total throughput per region is visualized in Figure 1.

A Herfindahl–Hirschman index (HHI) is constructed to serve as an indicator for the competitive environment facing ports. This index is calculated as the squared sum of all market shares within a specified proximity. This method is similar to that of De Oliveira and Cariou (2015). The index is constructed as follows:

\[
HHI_{i,j}(d) = \sum_j s_{j,t}^2 \text{ For } j = 1, 2, \ldots, N_i(d)
\]

where, \(d\) is the specified distance (kilometers) within which ports are assumed to be in competition for services, \(N_i(d)\) is the number of ports within the specified distance of port \(i\) and \(s_{j,t}\) is the market share of port \(j\) at time \(t\). The index is bounded from below by \(\left(\frac{1}{N_i(d)}\right)\), indicating perfectly symmetric market shares, and from above by 1, indicating a perfectly

<table>
<thead>
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<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
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</thead>
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<td>849,859</td>
<td>1,797,961</td>
<td>831</td>
<td>11,418,324</td>
</tr>
<tr>
<td>TA</td>
<td>778,020</td>
<td>1,271,267</td>
<td>6,000</td>
<td>7,654,073</td>
</tr>
<tr>
<td>BL</td>
<td>2,303</td>
<td>2,685</td>
<td>100</td>
<td>16,205</td>
</tr>
<tr>
<td>NC</td>
<td>27</td>
<td>34</td>
<td>1</td>
<td>228</td>
</tr>
<tr>
<td>MD</td>
<td>13</td>
<td>5</td>
<td>5.5</td>
<td>45</td>
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monopolistic market. To account for competition at different spatial levels, the index is constructed for three different values of $d$: 300, 500 and 700 km. To construct the indices, Euclidian distances are calculated for each port pair. The reason for constructing three distance levels rather than for example separate levels for each 100 km interval is related to the quality of the index. To identify differences in the effect of competition on efficiency for different spatial levels, it is necessary for there to be distinct differences between market concentration levels in the distance categories. The maximum cut-off value of 700 km is chosen to reflect a distance outside of which ports would generally not be considered to be in competition. Within 700 km, the intermediate cut-off values of 300 and 500 km are chosen because there is on average the same number of regional competitor ports within each these radiuses. For each distance level (300, 500 and 700 km), the average port in the sample faces competition from four additional ports. It should be noted that the HHI measure constructed only captures within-region competition, which is a limitation of this study. This means, for instance, that the competition faced by Mediterranean transshipment ports from African ports is not accounted for.

Disaggregating the HHI values by port region averages, it can be seen that the lowest levels of port concentration are found in the Hamburg-Le Havre region, indicating that this is the region where competition is the most intense. The region where market concentration is highest is the Mediterranean. These differences are shown in Figure 2.

An important determinant of port performance is hinterland market size. It can be expected, and has been shown in previous research (Yuen et al., 2013; De Oliveira and Cariou, 2015), that ports serving larger local markets tend to be more efficient. To account for this effect, it is necessary to provide some measure of hinterland market size. One option is to use population data as a proxy for market size (De Oliveira and Cariou, 2015). The use of such a proxy alone would implicitly state that the number of inhabitants in a port city or

Figure 1.
Total throughput volume development per region (measured as total number of TEUs with 2006 = 100)

Source: Own elaboration of Eurostat (2016b)
region mirrors the extent of business available to the port. A complementary measure of market size, used by Yuen et al. (2013), is regional or provincial economic output in the area of the port. Accordingly, this study uses two proxies to capture the effect of market size on efficiency. Gross regional product (GRP) series at the NUTS 3 level are gathered from Eurostat (2016c) and expressed in constant prices (in million EUR) to approximate the economic size of a port’s hinterland market. Population figures at the NUTS 2 level (the highest level available for sample period) are also gathered from Eurostat, (2016a) and used to provide a complementary measure of market size.

The dummy variable L is assigned to 1 for large ports, with an average annual throughput exceeding 1 million TEUs. It could be argued that any effect of scale on efficiency ought to be captured by a flexible-form production function. However, there is evidence in previous research (Tongzon and Heng, 2005; Cullinane and Song, 2006) of a residual relationship between estimated efficiency and size. One reason for such a relationship could be that size not only reflects scale effects on efficiency such as better usage of common infrastructure and a higher degree of intra-port competition but also serves as an indicator for unmeasured features of efficient ports such as apt locality and competence of management. Another reason for larger ports to be found more efficient is if the transshipment share of throughput is higher. As recognized by Serebrisky et al. (2016), transshipment cargo services typically requires a faster process of unloading and offloading, as well as a lesser use of storage and customs procedures. Ideally, it would be appropriate to account for these differences in service production characteristics by including a measure of transshipment cargo share in each port at each period. Such a measure is however not readily available. Instead, this effect is partially captured by the size measure L, as the largest ports in the sample are typically characterized as hubs and will in general serve a relatively high proportion of transshipment cargo.

Regional dummy variables are included to account for structural and institutional differences between different European regions as described in Section 2.2. Finally, a set of year-specific dummy variables is included to account for common industry shocks and business cycle effects on efficiency in the observed periods (Table II).

The empirical Cobb–Douglas and translog functions are (after log-linearization), respectively:
\[
\ln TP_{it} = \beta_0 + \beta_1 \ln TA_{it} + \beta_2 \ln BL_{it} + \beta_3 \ln MD_{it} + \beta_4 \ln NC_{it} + v_{it} - u_{it}
\]  

(10)

and:

\[
\ln TP_{it} = \beta_0 + \beta_1 \ln TA_{it} + \beta_2 \ln BL_{it} + \beta_3 \ln MD_{it} + \beta_4 \ln NC_{it} + \frac{1}{2} \beta_{11} \ln TA_{it}^2 + \beta_{12} \ln TA_{it} \ln BL_{it} + \beta_{13} \ln TA_{it} \ln NC_{it} + \beta_{14} \ln TA_{it} \ln MD_{it} + \frac{1}{2} \beta_{22} \ln BL_{it}^2 + \beta_{23} \ln BL_{it} \ln NC_{it} + \beta_{24} \ln BL_{it} \ln MD_{it} + \frac{1}{2} \beta_{33} \ln NC_{it}^2 + \beta_{34} \ln NC_{it} \ln MD_{it} + \frac{1}{2} \beta_{44} \ln MD_{it}^2 + v_{it} - u_{it}
\]  

(11)

With inefficiency component to be estimated simultaneously:

\[
u_{it} = \alpha_0 + \alpha_1 L_i + \alpha_2 \text{HHI}_i + \alpha_3 \ln Pop_i + \alpha_4 \text{Med}_i + \alpha_5 \text{HLH}_i + \alpha_6 \text{UK}_i + \alpha_7 \text{ScaBal}_i + \alpha_9 \text{D04}_i + \alpha_{10} \text{D06}_i + \alpha_{11} \text{D08}_i + \alpha_{12} \text{D10}_i + \alpha_{13} \text{D12}_i + W_{it}.
\]  

(12)

where, \(v_{it}\) is a normally distributed noise term and \(W_{it}\) is as defined in Section 3.2. All variables are as previously defined, and D04-D12 represent year-specific dummy variables. The functions are estimated as pooled panel models, with the simplifying assumption that for all \(i\) and \(t\), \(u_{it}\) and \(v_{it}\) are treated as independent. This specification treats inefficiencies as observation-specific rather than port-specific. An alternative estimation procedure would be to follow the example of Rodrigues-Álvarez and Tovar (2012) and introduce port-specific fixed effects. However, as the number of periods in the data is only six, this approach would lead to biases in both parameter and efficiency estimates (Greene, 2005). Instead, the time-invariant efficiency determinants corresponding to size and region can be seen to account for some (but not all) time invariant heterogeneity. A maximum likelihood estimator is applied, using a procedure based on FRONTIER 4.1 (Coelli, 1996). The estimates of technical efficiency for the \(i\)th port at time \(t\) can be retrieved as:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHI (d &lt; 300 km)</td>
<td>0.55</td>
<td>0.23</td>
<td>0.24</td>
<td>1</td>
</tr>
<tr>
<td>HHI (d &lt; 500 km)</td>
<td>0.38</td>
<td>0.17</td>
<td>0.16</td>
<td>0.99</td>
</tr>
<tr>
<td>HHI (d &lt; 700 km)</td>
<td>0.29</td>
<td>0.12</td>
<td>0.13</td>
<td>0.79</td>
</tr>
<tr>
<td>Population</td>
<td>2,570,344</td>
<td>1,800,684</td>
<td>377,235</td>
<td>8,377,810</td>
</tr>
<tr>
<td>GRP</td>
<td>29,225</td>
<td>27,787</td>
<td>1,991</td>
<td>167,106</td>
</tr>
</tbody>
</table>

\[ T\hat{E}_{it} = \exp[-u_{it}] = \exp[-\alpha Z - W] \]  

(13)

Which gives the ratio of actual level of production to maximum achievable production level given the observed input set and the production environment of the port. The purpose of estimating this particular system of equations is to test the following hypotheses for each spatial level of competition:

\[
H_0 : \alpha_2 = 0 \\
H_1 : \alpha_2 < 0 \\
H_2 : \alpha_2 > 0
\]

(14)

Where rejection of the null hypothesis in favor of \(H1\) indicates that, for the specified distance radius, market concentration and inefficiency are negatively related. This is analogous to the statement that competition and efficiency are negatively related. Rejection of the null in favor \(H2\) instead indicates that ports subject to a higher degree of competition are found to be more efficient, other things equal.

5. Results

In Table III, the estimation results of the stochastic frontier production function are presented. The two columns are results for the Cobb–Douglas and translog models [equations (10) and (11)]. A Likelihood–Ratio test confirms that the Cobb–Douglas functional form can be rejected in favor of the translog at a significance level of 1 per cent. The output elasticities, which can be conveniently read from the Cobb–Douglas estimation results, show

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cobb-Douglas</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.96*** (0.53)</td>
<td>14.73*** (4.48)</td>
</tr>
<tr>
<td>lnTA</td>
<td>0.46*** (0.04)</td>
<td>-2.99*** (0.85)</td>
</tr>
<tr>
<td>lnBL</td>
<td>0.22*** (0.09)</td>
<td>1.79 (1.23)</td>
</tr>
<tr>
<td>lnNC</td>
<td>0.47*** (0.06)</td>
<td>-0.21 (0.94)</td>
</tr>
<tr>
<td>lnMD</td>
<td>0.36* (0.21)</td>
<td>4.96** (2.34)</td>
</tr>
<tr>
<td>0.5 \times \lnTA^2</td>
<td>0.18*** (0.06)</td>
<td>0.13 (0.10)</td>
</tr>
<tr>
<td>lnTA \times lnBL</td>
<td></td>
<td>0.13 (0.10)</td>
</tr>
<tr>
<td>lnTA \times lnNC</td>
<td>-0.27*** (0.06)</td>
<td>-0.64*** (0.18)</td>
</tr>
<tr>
<td>lnTA \times lnMD</td>
<td>0.45 (0.30)</td>
<td>0.41*** (0.12)</td>
</tr>
<tr>
<td>0.5 \times lnBL^2</td>
<td>-0.04 (0.12)</td>
<td>0.05 (0.42)</td>
</tr>
<tr>
<td>lnBL \times lnNC</td>
<td>0.46* (0.27)</td>
<td>0.46* (0.27)</td>
</tr>
<tr>
<td>lnBL \times lnMD</td>
<td>-4.56*** (1.09)</td>
<td>-4.56*** (1.09)</td>
</tr>
<tr>
<td>0.5 \times lnMD^2</td>
<td>2.87*** (0.27)</td>
<td>2.87*** (0.27)</td>
</tr>
<tr>
<td>\sigma_u^2</td>
<td>0.94*** (0.02)</td>
<td>0.94*** (0.02)</td>
</tr>
<tr>
<td>\gamma</td>
<td></td>
<td>1.96*** (0.20)</td>
</tr>
<tr>
<td>LogLik</td>
<td>-612</td>
<td>-612</td>
</tr>
<tr>
<td>Num Obs</td>
<td>429</td>
<td>429</td>
</tr>
<tr>
<td>Mean efficiency</td>
<td>0.40</td>
<td>0.45</td>
</tr>
<tr>
<td>W-CRS</td>
<td>7.71***</td>
<td>55.64***</td>
</tr>
</tbody>
</table>

Table III. Results of production frontier estimation

Notes: ***, ** and * denote significance at the 1, 5 and 10% level, respectively
that an increase in 1 per cent in terminal area is roughly associated with a 0.46 per cent increase in throughput. The corresponding elasticities for berth length and number of cranes is 0.22 per cent and 0.47 per cent, respectively. The estimated output elasticity of maximum depth also has the expected positive sign but is not significant at a confidence level threshold of 5 per cent. For both specifications, an imposed restriction of CRS can be rejected. The sum of input parameters in the Cobb–Douglas function is 1.51, indicating increasing returns to scale in the production of port services. While the translog model parameters cannot be directly interpreted as output elasticities, partial elasticities can be calculated for each parameter. Such estimates are derived by calculating the percentage increase in fitted output resulting from a corresponding increase in a single input. The elasticities differ depending on the levels at which the variables are evaluated. Table IV (second column) shows these estimates when the median input values are used. This can be considered to approximate a typical port in the sample. While the elasticities can be interesting in themselves, they are not further discussed or analyzed in this study. Rather they serve as a robustness check to see that the estimated production functions appear to give reasonable results.

Table V details the results from simultaneous estimation of equation (12). The null hypothesis described by equation (14) is rejected in only one of the model variants. For competition measured within a range of 300 km, the positive and significant parameter estimate shows that a higher level of market concentration is associated with a higher level

<table>
<thead>
<tr>
<th>Input factor</th>
<th>Cobb-Douglas</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td>ε_TA</td>
<td>0.46</td>
<td>0.60</td>
</tr>
<tr>
<td>ε_BL</td>
<td>0.22</td>
<td>0.01</td>
</tr>
<tr>
<td>ε_NC</td>
<td>0.47</td>
<td>0.39</td>
</tr>
<tr>
<td>ε_MD</td>
<td>0.36</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Table IV.
Partial elasticities of output

Notes: Output elasticities from estimated production functions in Table III. For the translog model, elasticities are calculated for the variables evaluated at their median values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Translog (d = 300 km)</th>
<th>Translog (d = 500 km)</th>
<th>Translog (d = 700 km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>α0</td>
<td>4.85*** (1.86)</td>
<td>5.21*** (2.00)</td>
<td>5.60*** (1.79)</td>
</tr>
<tr>
<td>L</td>
<td>-3.81*** (0.75)</td>
<td>-3.96*** (0.94)</td>
<td>-3.57*** (0.68)</td>
</tr>
<tr>
<td>HHI (&lt; d)</td>
<td>1.23*** (0.39)</td>
<td>0.45 (0.50)</td>
<td>-0.95 (0.68)</td>
</tr>
<tr>
<td>lnPop</td>
<td>-0.32** (0.13)</td>
<td>-0.32** (0.14)</td>
<td>-0.33*** (0.13)</td>
</tr>
<tr>
<td>lnGRP</td>
<td>0.01 (0.09)</td>
<td>-0.01 (0.10)</td>
<td>0.04 (0.09)</td>
</tr>
<tr>
<td>Med</td>
<td>0.87*** (0.29)</td>
<td>1.05*** (0.33)</td>
<td>1.04*** (0.31)</td>
</tr>
<tr>
<td>HLH</td>
<td>1.55*** (0.38)</td>
<td>1.52*** (0.43)</td>
<td>1.22*** (0.40)</td>
</tr>
<tr>
<td>UK</td>
<td>-0.02 (0.36)</td>
<td>0.03 (0.39)</td>
<td>-0.06 (0.36)</td>
</tr>
<tr>
<td>ScaBal</td>
<td>0.73** (0.30)</td>
<td>0.72** (0.33)</td>
<td>0.60* (0.33)</td>
</tr>
<tr>
<td>D04</td>
<td>-0.03 (0.28)</td>
<td>0.01 (0.28)</td>
<td>0.02 (0.28)</td>
</tr>
<tr>
<td>D06</td>
<td>-0.16 (0.25)</td>
<td>-0.15 (0.27)</td>
<td>-0.17 (0.27)</td>
</tr>
<tr>
<td>D08</td>
<td>-0.15 (0.25)</td>
<td>-0.13 (0.27)</td>
<td>-0.15 (0.27)</td>
</tr>
<tr>
<td>D10</td>
<td>-0.06 (0.25)</td>
<td>-0.02 (0.27)</td>
<td>-0.04 (0.27)</td>
</tr>
<tr>
<td>D12</td>
<td>-0.02 (0.26)</td>
<td>0.05 (0.27)</td>
<td>0.05 (0.27)</td>
</tr>
</tbody>
</table>

Table V.
Inefficiency determinants

Note: *** and ** denote significance at the 1, 5 and 10% level, respectively.
of technical inefficiency. This means that an increased intensity of local competition is associated with significantly higher levels of efficiency. At the same time, such effects are not distinguishable for competition at wider spatial levels. The sign in front of market concentration within 500 km is positive, while the sign in front of market concentration within 700 km is negative. A negative effect of market concentration on efficiency would indicate that a higher level of competition between ports could cause inefficiency, which would be consistent with the conjecture that competition leads to overcapacity. Such a result is however not distinguishable in this analysis.

A marginal effect of local competition on estimated efficiency can be calculated using equations (12) and (13) to find that:

$$\frac{\delta \widehat{TE}_{i,t}}{\delta HHI(d < 300 \text{ km})_{i,t}} = - \alpha_2 \exp[-aZ - W] = - \alpha_2 \cdot \widehat{TE}_{i,t}$$

Such a calculation shows that a 1 percentage point increase in market concentration in the local area of a fully efficient port gives a predicted efficiency decrease of 1.2 percentage points.

The results also show that regional population size is negatively related to inefficiency, which implies that ports with larger hinterland markets tend to be more efficient. This is a reasonable result, given that serving a larger market should result in a more consistent level of demand and consequently better possibilities for accurate capacity planning. The effect of economic hinterland size, holding population constant, is not significantly different from zero. For the dummy variable distinguishing larger ports, the parameter estimates indicate large and significant differences in estimated efficiency. This indicates that larger ports, holding other factors equal, are estimated to be more efficient than smaller ports. This is in line with previous empirical results in the literature.

6. Possible implications for port policy and research
The finding that the intensity of local competition is positively related to port efficiency could be seen to suppress some of the concern that inter-port competition is in itself a cause of overcapacity. Further, it implies that levelling competition between ports could be a suitable direction for policy aimed to improve efficiency. While the analysis does not show any distinguishable negative effect of competition (for any spatial level) on efficiency in a panel that comprises a decade’s worth of observations, it is important to note that the somewhat crude nature of production frontier estimation makes it difficult to account for heterogeneity in port service production. With more refined data, particularly including the user side of production, the use of efficiency analysis techniques would be able to provide a higher level of accuracy and policy relevance in its results.

The results of the analysis conform in some respects to previous work and differs in some ways. The sign and significance of essential control variables, such as hinterland market size and port scale are largely in line with the literature. On the other hand, the finding that close-range competition is positively related to efficiency is a novel result. While Yuen et al. (2013) did find that the efficiency of Chinese container terminals improved with higher inter-port competition, this result was based on a pure distance measure and did not distinguish between different levels of competition. The result is also markedly different from that of De Oliveira and Cariou (2015), whose analysis suggested the opposite effect: a negative relationship between competition and efficiency. Whether any of these results hold generally is difficult to determine from the existing evidence. However, as the current study...
is focused on the European container port market specifically, it is arguably more telling of the situation pertaining to European container ports. The question is ultimately complicated by the fact that competition is difficult to accurately measure. Further research into the issue could do well to go beyond region- or distance-based measures of competition to account for the fact that proximity is not always a determinant of competitive intensity.

7. Conclusions

Proposals for a common ports policy framework in the European Union have advanced during the past decades. A recurring objective of such proposals has been to increase the autonomy of ports and to achieve more competitive markets. A concern that is often voiced with regard to this objective is that competition may exacerbate perceived problems of excess capacity in container ports, which can be harmful to the efficiency of the maritime transport system. In this study, the relationship between intensity of competition and technical efficiency is analyzed using a stochastic frontier approach and a dataset of 77 large European container ports over the period 2002-2012. The results indicate that there is no significant negative effect of competition on efficiency. In fact, for ports within a proximity of 300 km, a higher level of competition is found to be associated with a higher level of efficiency. The analysis suggests that reducing the market concentration by 1 per cent in the local area of a port may yield an efficiency increase of roughly 1.2 per cent. This implies that while excessive capacity expansion may sometimes result because of fierce inter-port competition, this does not appear to have been the general outcome for large European container ports during the studied period. The policy-relevant conclusion is that focusing efforts to reduce monopolistic powers of ports in local networks could be a viable way to improve efficiency. It is notable that this study, similar to most studies of port efficiency, would benefit from a greater level of access to micro-level data in ports. This includes turnaround times of vessels, terminal-level outputs and labor data. Gathering and using such data for the purpose of port efficiency analysis and policy evaluation is a difficult but recommendable task for future research.

References


**Corresponding author**

Axel Merkel can be contacted at: axel.p.merkel@himolde.no

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Prioritizing operational risks in container shipping systems by using cognitive assessment technique

Son Nguyen
Department of Maritime Transportation Economics, Vietnam Maritime University, Haiphong, Vietnam, and

HaiYan Wang
School of Transportation, Wuhan University of Technology, Wuhan, China and National Engineering Research Centre for Water Transport Safety, Wuhan, China

Abstract

Purpose – This paper aims to propose a technique based on cognitive assessments to quantify identified operational risks from the perspective of container shipping or logistics system administrators. The results derived from the risk quantification could be used to prioritize risks as well as support the decision-making process in risk prevention and mitigation.

Design/methodology/approach – This paper identified container shipping operational risks (CSORs) from a logistics perspective. A multivariate risk evaluation mechanism by fuzzy rules Bayesian network (FRBN) was established. An improved two-level parameter set based on the failure mode and effects analysis (FMEA) was used to support the input extraction process. By feeding cognitive assessments into the model, the identified risks are evaluated based on their utility values. An illustration example and a sensitivity analysis were carried out to justify and validate the proposed model.

Findings – The highest positions in the prioritized list of CSORs in the case study are dominated by risks in the physical flow with the first three are piracy and terrorism, force majeure and port congestion. The results derived from the case study with the satisfaction of all pre-defined axioms proved the feasibility and illustrated the functionality of the proposed risk assessment and prioritization technique.

Originality/value – Controlling risk is irrefutably a significant issue of container shipping and logistics management because of the inconsistency of risk definitions and the involvement of uncertainties. The proposed risk evaluation mechanism and the identified list of CSORs could be beneficial in system management, decision-making and reliability performance.

Keywords Risk analysis, Container shipping, Bayesian network, Risk identification, Decision support system, Operational risk, Risk prioritization

Paper type Research paper

1. Introduction

Despite a relatively short development history, a steadily thriving trend of the containerized shipping industry could be observed over the past few decades. A significant amount of 1.63 billion tons containerized freight volume accounted for 15 per cent of the international seaborne trade in 2015 (UNCTAD, 2015). In the process of globalization, container shipping has become the backbone of not only maritime transportation but also logistics networks (Guerrero and Rodrigue, 2014; Lam, 2013). As its gaining momentum and involvements in
different grounds, container shipping companies correspondingly have to deal with challenges of instabilities and disruptions.

As originated in the nautical discipline, “risk” has always been considered as a major influencing factor in maritime transportation (Aven, 2012b; Branch and Robarts, 2014). The attention of the academia toward risk management has been reflected in numerous studies in shipping and supply chain sector (Goerlandt and Montewka, 2015b; Eleye-Datubo et al., 2006; Barnes and Oloruntoba, 2005; Soares and Teixeira, 2001). Unexpected disruptive events have both directly and indirectly negative impacts on a company in multiple aspects (Chang et al., 2015; Bichou et al., 2014; Husdal and Brathen, 2010) such as unpunctuality of the liner schedule and damages or total loss of a shipment. They could lower the transportation service quality or even cause serious disruptions in a supply chain. The continuity and agility of the shipping network and interrelated systems would be heavily affected in a pervasive manner (Yang et al., 2010). Furthermore, the existence and possible consequences of risks required a managerial mechanism, which in turn requires adequate resources of a company to be distributed (Chang et al., 2014). Considering the significant role of container shipping in transport and the irreplaceable position of the transportation process in logistics planning, risk management could be regarded as an important sector in container shipping as well as supply chain management.

Risks in the container shipping industry exist in different aspects such as business, market, supply or demand. Owing to differences in involved factors and their affecting mechanisms, this paper concentrates on operational risks. Operational risks here could be understood as the risks that originated from activities in daily operations or businesses of the company (Mitra et al., 2015). Apparently, an adequate risk management plan is essential to reduce and control operational risks. However, to facilitate risk prevention/mitigation plans, the identification and analysis of related hazardous events (HEs) are inevitable. Additionally, resources allocated for risk management of a company are obviously limited to a time frame. Container shipping corporations are not exceptions. An effectively quantitative risk analysis model will not only provide insights into the risk situation of container shipping companies but could also motivate industrial stakeholders to take actions confidently as a decision support system (Alyami et al., 2014). Nevertheless, containers shipping is a complicated and somewhat fragmented system, which comprised physical movements, the associated information and responsibilities of multiple involved parties. Therefore, a decision support system, which could prioritize the identified operational risks based on a multi-dimensional base, is crucial regarding both financial performance and service quality of a container shipping company.

Despite the importance of prioritizing operational risks, only a limited number of studies attempted to comprehensively evaluate them or contribute analytical methodologies to determine their individual relative priorities (Tummala et al., 2011; Chang et al., 2015; Chang et al., 2014). One obstacle in container shipping risk assessment/prioritization is the scale and complexity of the system per se. It involves multiple parties (such as transporters, haulers, shippers, consignees, forwardingers and banks) with their responsibilities and processes (such as trucking, loading/unloading, shipping, payment and consolidating) varies with different operations, which are hard to investigate exhaustively. Bearing in mind the extraordinary relationship between container shipping and logistics operations, this paper continues to use the logistics perspective in the identification of operational HEs in container shipping as proposed in the study of Chang et al. (2015), Chang et al. (2014). By investigating the information flow, physical flow and payment flow in the logistics network, potential HEs in container shipping operations could be identified and categorized inclusively. The uncertainties attached to risks is another difficulty. It was agreed in risk
studies that they should be carefully taken into account for an adequately systematic risk approach (Levin, 2005; Aven and Zio, 2011; Cornell, 1996). The apparent significance of dealing with uncertainties in risk analysis has also been discussed and affirmed in the literature (Aven, 2012a, 2012b; Aven, 2010; Aven, 2016). The first category of uncertainty is described by Levin (2005) as “outcome uncertainty”. While the randomness in occurrence has already existed as an inherent characteristic of HEs, the impacts of a particular HE on a container shipping company are difficult to be measured. With the same HE (i.e. unpunctuality in information transmittance), the scenarios of both potential consequences and extent of severity are hard to be determined. The other category named “evidential uncertainty”, has its root in the application of subjective assessment on risk quantification. Despite the advantages of the experience and knowledge background of experts as well as the ability to use various evidences in making assessments, there is still certain vagueness in their judgments if the problem is excessively complex. Therefore, a manner by which the uncertainty of assessments from experts could be reduced is necessary. Dealing with these difficulties is crucial to achieving efficient risk quantification. This paper aims at answering two research questions:

RQ1. What parameters should be used to evaluate operational risks in container shipping?

RQ2. How to prioritize risks in container shipping effectively considering involved uncertainties?

The rest of paper is organized as follows. An analytical literature review is presented in Chapter 2. Chapter 3 focuses on the identification of typical HEs in container shipping operations from a logistics perspective based on clear risk concept and definition. A risk evaluation model powered by Fuzzy Rules Bayesian Network (FRBN) and improved risk parameters from Failure Mode and Effects Analysis (FMEA) is proposed in Chapter 4 and validated with a case study in Chapter 5. Finally, conclusions are drawn in Chapter 6.

2. Literature review
A significant attention was paid toward risks in maritime transport as well as container shipping by the academia (Goerlandt and Montewka, 2015b; Chang et al., 2015; Chang et al., 2014; Alyami et al., 2014; Yang et al., 2010; Notteboom and Vernimmen, 2009; Eleye-Datubo et al., 2006; Soares and Teixeira, 2001). Not only advances and variations in risk concepts and perspectives were made for purposes, but also there were developments in applying more efficient risk analysis methodologies (Goerlandt and Montewka, 2015b; Aven, 2012b). However, there are still glitches in maritime transport risk analysis studies. In fact, the definition of risk definitely affects the result of the risk identification process. It was indicated by Goerlandt and Montewka (2015b) that one of the most foundational existing issues is the underestimation and fragmentation of risk definitions. This problem is considered as the main cause of terminological misunderstanding and limitations in risk-related communications (Hampel, 2006; Kaplan, 1997). To clarify the base for risk identification, the used risk concept and perspective toward it in this study are introduced in Chapter 3.

In a strong frequentist viewpoint, risk evaluation strictly relies on historical statistics and objective treatments of these samples. However, this approach manner could not be implemented meaningfully in various risk assessment contexts where there is uniqueness/randomness in the occurrence and development of potential HEs (Cornell, 1996; Apeland et al., 2002; Aven and Zio, 2011; Li et al., 2012). Additionally, as Bjerga and Aven (2015)
denoted in an adaptive risk management example, the dynamics of risk should be noticed in the analyzing process. Therefore, using entirely historical, even a continuously updated data as experience-wise risk description, seems to make the analysis process always left behind by the real risk situation. In opposite, using subjective assessments in measuring risk as a constructivist approach returns a cognitive, socialized and sometimes predictive view of risks (Goerlandt and Montewka, 2015b; Apeland et al., 2002). Nevertheless, the objective existence of risks is still undeniable, and the subjectivity should only enter the scene when attempts were made to measure analyze risks (Aven, 2012b; Aven, 2010; Aven et al., 2011).

As a result, differences among risk concepts and definitions of risk levels as individual mind constructs is a difficulty in risk assessment. Risk studies that used expert assessments usually attempt to establish “standards” such as risk concept or risk measuring instruments to calibrate assessing system or use iterative elicitation procedure to limit biases (Apeland et al., 2002; Aven, 2012b). By facilitating specification in risk description and assessment, this study uses the subjective probability from judgments of experts as the primary source of inputs for the container shipping risk evaluation process.

Even though studies have been conducted on the container shipping risks, an inclusive identification of operational risks which concerns the relationship between container shipping and logistics network has just been proposed recently (Chang et al., 2015; Chang et al., 2014). Although the logistics perspective in container shipping risks identification was proved as applicable and effective, problems related to the risk analysis methodology are still observable in these studies. The risk parameters that only consist of likelihood and consequences seem excessively general and inadequate in risk evaluation. Furthermore, using risk mapping and average risk scale or stochastic dominance method where expert judgments are treated as crisp numbers without an efficient mechanism to handle uncertainties or vagueness also affects the result of risk evaluation process. This study concentrates on a more comprehensive and specific risk parameter set for risk assessment in container shipping operations from a logistics perspective.

The Failure Mode and Effects Analysis (FMEA), first developed by the US Armed Force in 1950s, is a useful assessment tool in product or system safety and reliability analysis (Carlson, 2012). The traditional risk quantification approach of FMEA used the product of likelihood, consequence severity and the probability of being undetected to prioritize risks – risk priority number (RPN). Owing to its simplicity and easiness in implementation, FMEA was applied widely in the maritime sector including ship design and classification (IMCA, 2002), offshore engineering system (Yang and Wang, 2015), maritime transportation system (Goerlandt and Montewka, 2015a). There is also an FMEA review paper of Liu et al. (2013) includes 75 studies about FMEA in risk evaluation. However, this approach manner is criticized by literatures as: ignoring linguistic variables from expert (Wang et al., 2009; Garcia et al., 2005); shortage of an universal scale (Kumru and Kumru, 2013; Garcia et al., 2005); limitation of RPN as a proper and meaningful risk measurement (Kumru and Kumru, 2013). To tackle these deficiencies, methods were complementarily applied to enhance FMEA such as fuzzy set theory (Zadeh, 1965); Data Envelopment Analysis (Garcia et al., 2005); Artificial Neural Network (Rafie and Samimi Namin, 2015) and various others.

As a proposed method to enhance the risk quantification feature of FMEA, risk evaluation model of Yang et al. (2008) using Bayesian reasoning with fuzzy rules base (FRB) is proved to be effective in calculating failure priority value based on FMEA risk attributes (Alyami et al., 2014). However, its applicability is heavily affected by the bulky and arduous establishment of the IF-THEN FRB with a rational structure of degree of belief (DoB). Based on that, Alyami et al. (2014) proposed a more “automatic” and “balanced” mechanism of IF-THEN rules generation.

For example:
IF \textit{likelihood} is Low; \textit{consequence severity} is Low; \textit{being detected probability} is Medium and \textit{impact on port resilience} is High THEN risk level is Low with 50\% (2/4), Medium with 25\% (1/4) and High with 25 \% (1/4) DoB.

However, the meaning of the attribute “impact on port resilience” which was introduced as a separated factor seems to overlay with “consequence severity” as one of the multiple direct adverse effects of an HEs on the system. This overlap certainly affected the accuracy of the risk index (RI) results. The study of Yang \textit{et al.} (2013) also used FRBN in prioritizing port security vulnerabilities. Nevertheless, the criticality evaluations derived as the results of the fuzzification process were limited in just two states, while in fact, the values regarding risk parameters such as “damage capability” or “recovery difficulty” could be in a much wider range. Given the existing difficulties and limitations as well as advantages of prior studies, this paper will introduce a novel risk technique which comprised an improved risk parameter structure based on FMEA and its integration into an FRBN model for container shipping risk evaluation.

3. Operational risks in container shipping
As an important part of risk management, risk identification is heavily affected by the used concept of risk (Aven and Krohn, 2014; Aven, 2012b). In fact, the application and significance of a risk analysis study largely depend on risk communication. However, applied risk concepts are diversified, weakly justified both in general (Aven and Zio, 2014; Aven, 2012b) and in maritime transportation particularly (Goerlandt and Montewka, 2015b). Inconsistent risk concept on top of terminological misunderstandings undeniably obstruct risk analysis models from actual effective applications. Also, an unreasonable or unjustified risk perspective could seriously misguide the decision-making process (Aven, 2012b). Answer the reasonable call of Goerlandt and Montewka (2015b), Aven (2012b) for a clearer theoretical base in risk analysis papers, the applied concept of risk is introduced before the risk identification process.

3.1 Concept of risk – risk definition and perspective
Numerous risk concepts have been developed throughout history. They could be traced back to different sourcing environment (such as economics and engineering). In the study of Aven (2012b), nine groups of risk definitions are classified into six development paths historically, then argued and analyzed to examine their suitableness. The result indicates that risk concepts are now developing toward a general and holistic manner, able to capture the risks in multiple disciplines. Among groups of risk definitions, $R = C \& U$ which defines risk as combination of Consequence (C) and Uncertainty (U) are pointed out as the most appropriate concept (Aven, 2012a; Zio, 2007; Aven, 2012b). In addition, this approach usually incorporate the HEs/threats (A) as an prior element lead to specific consequences (Aven and Krohn, 2014; Aven and Reniers, 2013; Aven, 2011). Based on this risk concept, the definitions of risk put forth by this paper will be established and used throughout this study. The specialized definition of operational risk is adapted from the study of Manuj and Mentzer (2008) with minor modification to be in line with the proposed Risk definition:

- \textit{Risk definition}: The presence of potential HEs, which may lead to actual negative consequences and uncertainties involve in this transformation.
- \textit{Operational risk definition}: The existence of risks which may negatively affect the internal ability of the company to maintain its goods/services at a certain level of quality, quantity or profitability.
This definition describes risk as a qualitative concept by which facilitate the distinction between risk definition and measurement. The perspective toward risk of this definition is clear. It recognized the objective existence of risk as well as the uncertainty as a natural characteristic of risk. Probability here is not viewed as a component of the risk concept per se but used as a tool for risk measurement/description through informed judgments provided by multiple experts – intersubjective probability (Aven et al., 2011).

3.2 Identification of hazardous events in container shipping operations

The role of container transport in logistics systems is irreplaceable. For the sake of risk prioritization and prevention or responses to ensure the reliability and seamlessness of the container transport system, the existing operational risks should be identified inclusively. This problem could be solved adequately by the implementation of a logistics viewpoint toward container shipping operations. Essentially, activities in container shipping could be divided into three flows: Information, Physical and Payment (Figure 1). This study will use the manner proposed by Chang et al. (2014), Chang et al. (2015), Chang et al. (2016) to identify risk in container shipping operations systematically from previous literatures. Owing to the rarity of literature on container shipping operational risk, the reviewing process will also include operational risk studies on container logistics/container supply chain.

3.2.1 Information flow. The information flow is closely related to the visibility and collaboration performance of the logistics network as well as container shipping (Lotfi et al., 2013). The flow is initiated by the trade agreements between consignors and consignees. To assure functional connections for an operation, a complex information sharing/transmitting network is created between multiple parties in the system (Figure 1). As the development of logistics networks to provide more features such as door-to-door services, distribution processing or warehouse operations, the complexity of the information flow is also increased, put it under multiple risks (Madenas et al., 2014). By reviewing literature in the field, Madenas et al. (2014) pointed out insufficiencies of communications among heterogeneous systems such as interruptions or overlaps. Large time-lags between receipt and transmission has also been considered as another cause of information delay (Metters, 1997; Angulo et al., 2004). The number of documents and processes related to multiple activities and responsibilities of parties in container transport system exposes the system to the risk of delays, for e.g. formalities of the port authority, customs clearance and documents issuing (Bichou et al., 2014).

Figure 1.
Three flows in a typical container shipping system
The integrity and sufficiency of information is another aspect. For example, in many cases, only a generic description of consolidated cargoes in a Less than Container Load (LCL) shipment are provided. The missing of other detailed but vital information about individual shipments may mask a risk to the ship and its crew (Bichou et al., 2014). Bichou et al. (2014) also described other cases of information asymmetry/incompleteness in documents issuing, cargoes declaration and crew’s ability by which highlights the marine safety’s compromises with accidents and inadequacies. Lack of information security could lead to vulnerability of the data transference. Leaked or tampered data might affect the accuracy and integrity of the information (Chang et al., 2015). Subsequently, this could expose a container shipping company to the hazard of information technology (IT) sabotage or unauthorized accesses into its database. The incompatibility of data forms using in systems is another source of data errors and inaccuracies (Tummala et al., 2011). Chang et al. (2015) also discovered that larger shippers might use their advantages in negotiation to request more, even unreasonable information from the shipping company or intentionally declare inaccurate shipment information.

IT system malfunctions could disrupt the continuity of data flow and pervasively affect other flow in a supply chain. The breakdowns of IT could be a possible factor (Tummala et al., 2011). Also, technical problems could also be triggered by human errors in interactions with the IT system, and according to Howarth (2014), 95 per cent of all IT security incidents involve human error. Inefficiencies in IT system operations will definitely put the timeliness and accurateness of the data transmission at risk.

3.2.2 Physical flow. Unlike the complexity of information flow, the actual movements of containers seem to be more straightforward (Figure 1). However, they also have to face a large number of risks, which come from multiple influencing factors including shipping density, sea condition or human errors, which could be divided into two primary categories: Transportation delay and Losses/damages of goods/assets. Transportation delays might have negative effects on the logistics cost of the shippers and also lower the liner’s reputation (Notteboom, 2006). As critical nodes in the transport network, the operational performance of ports/terminals decisively affects the quality of carriage services. Notteboom (2006) identified the three typical risks in ports/terminals as in Table I. Based on the sea transportation situation in Norway, Husdal and Brathen (2010) indicated several risks that could lead to disruption of incoming and outgoing physical flow. In addition, the uncertainties in demand for empty containers and the dispatching ability of the shipping company make container shortage another risk (Song et al., 2005; Chang et al., 2015). The study of Song et al. (2005) highlighted the importance of empty containers, as well as fleet deployment, thus expressed the potential failures in capacity management. Delays could also be raised from events in which cargoes or vessels are detained by authorities e.g. customs clearance or Port State Control (PSC) inspection (Tummala et al., 2011; Bichou, 2009).

There are also HEs that could cause direct physical damages/losses to vessels, crews or goods. The consequences of these risks include human and financial losses, compromised company image, legal liabilities. Accidents and inefficiencies in the operations of both landside and seaside such as maritime collisions, road accidents, traffic jams or cargo handling operations could be considered as a substantial type of risk (Bichou, 2009; Husdal and Brathen, 2010; Goerlandt and Montewka, 2015b). Transporting containerized dangerous goods is regarded as another specific risk with its uncertain and potentially massive consequences to human, environment and infrastructures (Chang et al., 2015; Husdal and Brathen, 2010). With cold chain logistics, maintaining a specific range of temperature inside reefer containers is vital. Failures in keeping a stable and continuous electricity supply could
### Table I.
Identified risks in container shipping operation

<table>
<thead>
<tr>
<th>Flows</th>
<th>Groups</th>
<th>HEs</th>
<th>HE code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information</td>
<td>Information delay</td>
<td>Difference in communication interface</td>
<td>ID1</td>
</tr>
<tr>
<td>risk</td>
<td></td>
<td>(Tummala et al., 2011; Madenas et al., 2014; Metters, 1997; Chang et al., 2015)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unpunctuality in information transmission</td>
<td>ID2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Angulo et al., 2004; Chang et al., 2015; Metters, 1997)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Information inaccuracy</td>
<td>Unexpected delay in documents or formalities</td>
<td>ID3</td>
</tr>
<tr>
<td></td>
<td>or incompletion</td>
<td>(Bichou et al., 2014; Husdal and Brathen, 2010)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Information system insecurity/vulnerability</td>
<td>II1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Chang et al., 2015)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Information</td>
<td>Information asymmetry/incompleteness</td>
<td>II2</td>
</tr>
<tr>
<td>technical risk</td>
<td></td>
<td>(Angulo et al., 2004; Bichou et al., 2014)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lack of information standardization and compatibility</td>
<td>II3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Tummala et al., 2011)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Extra information inquiries from shippers</td>
<td>II4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Chang et al., 2015)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Shippers hiding cargo information (non-declare)</td>
<td>II5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Chang et al., 2015; Bichou et al., 2014)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>IT infrastructure</td>
<td>IT infrastructure deficiencies (Tummala et al., 2011)</td>
<td>IT1</td>
</tr>
<tr>
<td></td>
<td>deficiencies</td>
<td>(Howarth, 2014)</td>
<td>IT2</td>
</tr>
<tr>
<td>Physical risk</td>
<td>Transportation delay</td>
<td>Port strike, unrest or war situation (Notteboom, 2006; Tummala et al., 2011; Husdal and Brathen, 2010)</td>
<td>TD1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Port congestion (Notteboom, 2006; Bichou, 2009)</td>
<td>TD2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unexpected port/terminal cargo handling productivity</td>
<td>TD3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Notteboom, 2006; Tummala et al., 2011)</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Unexpected slow steaming or behind voyage schedule</td>
<td>TD4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Notteboom and Vernimmen, 2009; Husdal and Brathen, 2010)</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Container shortage (Song et al., 2005; Chang et al., 2015)</td>
<td>TD5</td>
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<tr>
<td></td>
<td></td>
<td>Inflexibility fleet operation and management (Song et al., 2005)</td>
<td>TD6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cargos or ships being detained by authorities (Tummala et al., 2011; Bichou, 2009)</td>
<td>TD7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Force majeure (Branch and Robarts, 2014; Husdal and Brathen, 2010; Tummala et al., 2011; Notteboom, 2006)</td>
<td>TD8</td>
</tr>
<tr>
<td></td>
<td>Loss/damage of goods/</td>
<td>Inland traffic accidents and system inefficiencies</td>
<td>TL1</td>
</tr>
<tr>
<td>assets</td>
<td>assets</td>
<td>(Bichou, 2009; Husdal and Brathen, 2010)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maritime accidents (Goerlandt and Montewka, 2015b; Husdal and Brathen, 2010)</td>
<td>TL2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Damage to containers or cargo handling operations</td>
<td>TL3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Husdal and Brathen, 2010)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Damage caused by transporting dangerous goods (Husdal and Brathen, 2010; Chang et al., 2015; Bichou, 2009)</td>
<td>TL4</td>
</tr>
</tbody>
</table>

(continued)
heavily affect the quality of cargoes in containers (Chang et al., 2015). The risk of theft and cargo tampering are noteworthy because of its occurrence potentials in almost every process of container movements (Husdal and Brathen, 2010; Bichou, 2009). Finally, piracy and terrorism have always been considered as a well-noted security issue in maritime transport (Chang et al., 2015; Bichou, 2009).

3.2.3 Payment flow. Unlike risks in information and physical flow of the container shipping system, consequences of risks in the payment flow have direct impacts on the financial performance of shipping companies e.g. poor liquidity, distraintment. Delays of payment are mostly caused by mistakes of the payers (based on different trade terms) and unrealized contract with partners (Notteboom and Vernimmen, 2009; Chang et al., 2015; Tummala et al., 2011). Also, Tummala et al. (2011) as well as Manuj and Mentzer (2008) indicated that using weak currency in trading could cause financial losses in international businesses. Risks attached to the operational costs which are heavily affected by the fuel price are considered significant (Tummala et al., 2011; Notteboom and Vernimmen, 2009; Manuj and Mentzer, 2008; Ghosh et al., 2015). Financial difficulties or bankruptcy faced by a partner in the system also might cause payment risks to other parties (Husdal and Brathen, 2010; Tummala et al., 2011; Manuj and Mentzer, 2008). Furthermore, wrong choices of partners, which are having bad credit, might give back the partial or total loss of payments (Tummala et al., 2011; Chang et al., 2015). Break of agreement or contract, reducing container volume or intentional abandonment of containers at the port of destination also raise the

<table>
<thead>
<tr>
<th>Flows</th>
<th>Groups</th>
<th>HEs</th>
<th>HE code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payment risk</td>
<td>Payment delay</td>
<td>Payment delay from partners or shippers (Tummala et al., 2011; Chang et al., 2015)</td>
<td>PP1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unrealized contract with partners (Notteboom and Vernimmen, 2009; Chang et al., 2015; Tummala et al., 2011)</td>
<td>PP2</td>
</tr>
<tr>
<td></td>
<td>Decrease or total loss of payment</td>
<td>Exchange rate fluctuation during payment process (Chang et al., 2015; Tummala et al., 2011; Manuj and Mentzer, 2008)</td>
<td>PD1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Unexpected rise in operational cost (Tummala et al., 2011; Notteboom and Vernimmen, 2009; Manuj and Mentzer, 2008; Ghosh et al., 2015)</td>
<td>PD2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Payers’ financial difficulties or bankruptcy (Husdal and Brathen, 2010; Tummala et al., 2011; Manuj and Mentzer, 2008)</td>
<td>PD3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Shippers breaking the contract/reducing the container volume (Chang et al., 2015)</td>
<td>PD4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Having partners with bad credit (Tummala et al., 2011; Chang et al., 2015)</td>
<td>PD5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Containers are abandoned at the port of destination (Chang et al., 2015)</td>
<td>PD6</td>
</tr>
</tbody>
</table>

Table I.
potential of financial losses or non-payment (Chang et al., 2015). Finally, most common operational risks in container shipping are identified and listed in Table I.

4. Risk evaluation methodology
Bayesian subjective probability is considered as the most common method of handling epistemic uncertainty (Aven, 2016). The method applied in this study is inspired by prior studies that used FRBN to express the causal dependencies of componential factors on the overall risk level of each HE (Yang et al., 2008; Alyami et al., 2014). However, the risk measuring parameter set is improved on the basis of FMEA with the presence of two parameter levels (Figure 2). The utility values of risk levels computed from FRBN model will be used for HEs prioritization. Finally, the model will be validated by a sensitivity test.

4.1 Improved risk parameter based on failure mode and effects analysis
The traditional quantification approach of FMEA used only three parameters: Likelihood of occurrence (L); Severity of consequence (S) and Probability of being detected (P) to measure Risk level (R) by using number assignment. This approach ignored the meaningful utilization of linguistic variables in interaction with expert and lack of a universal scale, hence became severely subjective (Alyami et al., 2014; Rhee and Ishii, 2003; Garcia et al., 2005). Furthermore, the RPN is only the product of ordinal numbers and has poor performance in risk prioritization owing to results repetition. Additionally, the excessive generality presented by the traditional assessment parameters could not facilitate uncertainty treatment in the judgments assigning process. It is obviously unrealistic and infeasible for experts if the target object for assessment is excessively general or complicated (Aven, 2012b). This study will use a more accurate and tailor-made FMEA approach for container shipping by adding a secondary level of risk parameters into the existed parameter structure.

The consequences of an HE from the view of a shipping company could be separated into three secondary aspects: Financial impact (F), Reputational impact (I) and Operational impact (O). Financial impacts could be understood as the HE’s effects on the financial flow of the company and could be expressed through financial losses e.g. fines, additional fees, loss of infrastructures and compensations. The reputational impact expresses the damages of the HEs on the company image and credibility in the view of customers or partners, which could be observed through complaints, break of contract, agreement or decrease of stock price. An HE might also affect the operational plans of a shipping company in the sense that voyage schedule could be forced to be adjusted, reallocation or intensification of human resource in response to the consequences.

![Figure 2. Improved parameter structure based on FMEA for container shipping operational risks](image-url)
The ability of a company in HE detection is presented as Level of detection (D). A more hidden HE is obviously more dangerous if it is harder to be prevented and be aware of by the risk-bearers than others. In container shipping, besides the probability of being undetected (U), the lateness of detection (T) is also noteworthy, as it negatively affects the attempts of companies in response and limits the damages which caused by HEs. For example, lateness in the detection of missing required documents or liquidity problems could cause great financial and operational losses for a shipping company. In summary, the parameter set established for experts to assess each HE is as in Figure 2.

4.2 Fuzzy rules Bayesian network model building process and risk prioritization
To build up an FRBN model which can evaluate operational risks in container shipping, two important parts must be determined. First, the causal network structure must express the conditional relationships among related factors, especially the direct and indirect dependencies of the risk level on indicated parameters. The second component is the conditional probabilities which quantitatively convey these relationships. In this study, an IF-THEN FRB is constructed for this purpose.

4.2.1 Directed acyclic graphs building. Directed Acyclic Graphs (DAG) is an intuitive tool which provides a visual expression of a causal network (Kjærulff and Madsen, 2013). Based on the introduced risk parameter structure, DAGs which express the structure of dependency of the risk level of factors and the among factors for individual HEs could be constructed. They include two primary types of components: nodes and links. In this case, while each node is assigned to an aspect/factor, links among these nodes explain the dependencies in the causal network which follow the structure as the hierarchy graph in Figure 2. For example, the HE ID1’s risk level has a DAG as in Figure 3.

In this network, the risk level of ID1 is represented by a “leaf node” which does not have any child node. All secondary parameters (F, I, O, U, T) and Likelihood of occurrence (L) are assigned to nodes that are called “root nodes”, as they do not have any parent node (Yang et al., 2008). These nodes are also the gateways where the aggregated assessments are fed into the network as inputs.

4.2.2 Establishment of conditional probability tables through IF-THEN fuzzy rules base. IF-THEN rules are used in this paper as a tool to convey the quantitative conditional relationship between designated nodes. A system of IF-THEN rules based on the study if Alyami et al. (2014) could be established with a belief structure. For example:

For D, which depends on U and T: IF U is Low and T is Low THEN D is Low with 100% (2/2) DoB, Medium with 0% (0/2) DoB and High with 0% (0/2) DoB.
For S, which depends on F, I and O: IF F is Low, I is Medium, and O is Medium THEN S is Low with 33.33% (1/3) DoB, Medium with 66.67% DoB (2/3) and High with 0% (0/3) DoB.

For R, which depends on L, S, and D: IF L is Low, S is Medium and D is High THEN R is Low with 33.33% (1/3) DoB, Medium with 33.33% (1/3) DoB and High with 33.33% (1/3) DoB.

As there are three states of each node in the network (low, medium and high), the number of rules for each parameter could be calculated. Level of detection (D) has nine rules \(3^3\), while severity of consequence (S) and risk level (R) has 27 rules \(3^3\). Based on these rules, CPT for each child node in the FRBN could be built. An example of CPT for R in case L is low is in Table II.

### 4.2.3 Prioritization of the hazardous events using rational degree of beliefs and proposed fuzzy rules Bayesian network model.

To simplify the demonstration of the calculus process, the notions of the risk parameters and nodes assigned to them are used interchangeably in this paper \((R, L, S, D, U, T, O, I, F)\). Inputs fed into the FRBNs are aggregated rational distributions as expert judgments for individual root nodes at each state (low, medium and high). Denote \(r, l, s, d, u, t, o, i, f\) are indicators by which states of \(R, L, S, D, U, T, O, I, F\) are displayed, they might take one of these three values: 1 (Low), 2 (Medium) or 3 (High). The marginal probabilities of \(D\) as the child node of \(U\) and \(T\); \(S\) as the child node of \(O, R\) and \(F\); \(R\) as the child node of \(L, S\) and \(D\) could be calculated as the equation (1), (2) and (3), respectively:

\[
p(D_d) = \sum_{u=1}^{3} \sum_{t=1}^{3} p(D_d | U_u, T_t)p(U_u)p(T_t) \\
\text{(d = 1, 2, 3)}
\]

\[
p(S_s) = \sum_{o=1}^{3} \sum_{i=1}^{3} \sum_{f=1}^{3} p(S_s | O_o, I_i, F_f)p(O_o)p(I_i)p(F_f) \\
\text{(s = 1, 2, 3)}
\]

\[
p(R_r) = \sum_{l=1}^{3} \sum_{s=1}^{3} \sum_{d=1}^{3} p(R_r | L_d, S_s, D_d)p(L_d)p(S_s)p(D_d) \\
\text{(r = 1, 2, 3)}
\]

By getting the probability of \(R\), a risk ranking index (RI) could be developed by using utility values (UV) for each state as the equation (4) (Alyami et al., 2014; Yang et al., 2008). This study uses \(UV_{R_1} = 1; UV_{R_2} = 10; UV_{R_3} = 100\) (Alyami et al., 2014). An HE with higher RI

<table>
<thead>
<tr>
<th>Likelihood of occurrence</th>
<th>Severity of consequence</th>
<th>Level of detection</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td></td>
<td>Low</td>
<td>1</td>
<td>2/3</td>
<td>1/3</td>
<td>2/3</td>
<td>1/3</td>
<td>1/3</td>
<td>2/3</td>
<td>1/3</td>
<td>1/3</td>
</tr>
<tr>
<td>Medium</td>
<td></td>
<td>Medium</td>
<td>0</td>
<td>1/3</td>
<td>2/3</td>
<td>1/3</td>
<td>2/3</td>
<td>1/3</td>
<td>0</td>
<td>1/3</td>
<td>0</td>
</tr>
<tr>
<td>High</td>
<td></td>
<td>High</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1/3</td>
<td>1/3</td>
<td>1/3</td>
<td>2/3</td>
<td>0</td>
</tr>
</tbody>
</table>
is considered having higher risk level. Based on $RI$ values, identified risks could be prioritized.

$$RI = \sum_{r=1}^{3} p(R_r)UV_{R_r}$$  \hspace{1cm} (4)

4.3 Validation method
Sensitivity analysis is one of the most popular mechanistic validation method used in FRBN studies (Alyami et al., 2014; Yang et al., 2008). Inputs fed into root nodes will be adjusted successively and resulting changes of related child nodes will be recorded. To test the reasonability of the constructed model, the tendency in variations as well as the accuracy of implemented CPTs, three axioms as follow could be used (Alyami et al., 2014; Yang et al., 2008):

1. Axiom 1. An increase/decrease in the prior DoB of parent nodes should certainly result in a relative increase/decrease in the posterior DoBs of the child nodes and finally, the $RI$ value based on the DoB of the leaf node.

2. Axiom 2. The total influence magnitudes of multiple probabilities adjustments of a set of nodes, which have the same effects (positive or negative) on its child nodes and the leaf node, should always be greater than the one of its any subset.

3. Axiom 3. The tendency of variations in probabilities with any adjustment should be in accordance with the analyzed results of influencing mechanisms (positive or negative).

5. Illustration example and methodology validation
5.1 Illustration example – a case study
The structure of the expert committee is decided based on several arguments. It should be noted here that increasing the number of rational distributions for a judgment does not ensure any “accuracy” improvement. However, there are significant threats of quality degradation owing to multiple factors. Statistically, a raise of the sample size will definitely bring more noise to the model (Rae and Alexander, 2017). Furthermore, this problem could be exacerbated by the fact that the reliability of the chosen “experts” largely depends on the cognitive ability reflected in the mental models which are, in turn, heavily affected by the situation understandings as well as the accumulated experience (Rae and Alexander, 2017). Putting more in quantity instead of quality in building expert committee is, therefore, not recommended by this research. To demonstrate the application of the proposed model, a case study is carried out on an anonymous container shipping company with the participation of three experts in different positions as the study of Alyami et al. (2014).

The subject for research is a Vietnam shipping company located in Haiphong, a major port city and planned logistics center in the northern region of the country. Bulk shipping is the primary and traditional market of the company. However, short-sea container shipping between Vietnam, China or other ASEAN countries is also an important business segment that the company wants to sustain. With a total fleet of 21 vessels and 6 of them are feeder container ships, the company mainly provides its service for Japanese and Korean industrial
groups. Therefore, the company is considered by the author as an acceptable case study. A questionnaire was designed to collect subjective assessments from these experts (α, β and γ). They all have more than ten years of experience working in container shipping field. To support the subjective assessing process, a table of concepts for individual states of each input parameter is discussed and determined deliberatively (Table III).

In the questionnaire, experts are asked to provide their subjective assessments in the form of rational distributed DoB for each state of individual identified HEs as mentioned in Section 4. Next, a simple average calculation (arithmetic mean) is used to aggregate these raw values. These aggregated DoBs from experts are used as the input for FRBN to calculate the RI value of individual HEs. The HUGIN Expert software is used in Bayesian probability calculus (Alyami et al., 2014; Kjærulf and Madsen, 2013). Input DoBs of root

<table>
<thead>
<tr>
<th>Risk parameters</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>Rare occurrence, once every six months or less often</td>
<td>Occurs sometimes, from twice every six months to once every three months</td>
<td>Often occurs, twice every three months or more often</td>
</tr>
<tr>
<td>F</td>
<td>Slight or no impact considered the return from freight or below US$10,000/time</td>
<td>Significant impact considered the return from freight or from US $10,000 to 50,000/time</td>
<td>Heavy impact on the return from freight, causes loss or above US$50,000/time</td>
</tr>
<tr>
<td>I</td>
<td>Slight or no impact on the relationships (partner or customer), no complaint received, no observed impact on the stock market</td>
<td>Noticeable impact on the company’s relationships, received complaints or causes decrease in stock price but considered recoverable in short term</td>
<td>Heavy impact on the company’s relationships, losses of partner(s), customer(s) or breaks of contract or agreement, causes significant decrease in stock price</td>
</tr>
<tr>
<td>O</td>
<td>Slight or no impact on the planned voyage or ship schedule, reallocation or intensification of personnel is unnecessary</td>
<td>Causes changes in the planned voyage itself or ship schedule of the line, causes minor reallocation or intensification of related personnel</td>
<td>Heavy impact on the company’s vessel management operation, causes changes in operation plan of other ship(s) or line(s), reallocation or intensification of in-charge personnel</td>
</tr>
<tr>
<td>U</td>
<td>High predictability, significant chance of detection in the preparation or planning stage of the operation, legs or voyage, the mitigation or prevention methods are effectively implemented</td>
<td>Difficult to identify during the preparation or planning stage of the operation, legs or voyage, the mitigation or prevention methods are not yet implemented or implemented but with limited effect</td>
<td>Impossible or extremely difficult to foresee during the preparation or planning stage of the operation, legs or voyage, the mitigation or prevention methods are not yet discovered by the operation manager nor planned for implementation</td>
</tr>
<tr>
<td>T</td>
<td>High chance of detection during the operation or at the early phase when the failure is about to begin or already caused impacts but the severity is still minor and recoverable (low)</td>
<td>Harder to detect, often during the operation or can only be detected when the failure is already caused medium level severity (one or more in three listed above)</td>
<td>Impossible or extremely hard to detect during the operation or can only be detected when the failure has already caused high-level severity (one or more in three listed above)</td>
</tr>
</tbody>
</table>

**Table III.** Concepts of individual states for each input parameter
nodes as well as other nodes in the network could be displayed as a result of the calculation process. An example of the HE ID1 is presented in Figure 4.

After getting risk level in the form of DoB in three states, Equation (4) is used to calculate $RI$ values. For example, with ID1, its index value will be calculated as: $RI_{ID1} = 60.74\% \times 1 + 26.11\% \times 10 + 13.15\% \times 100 = 16.3684$. All HEs identified in Table I are prioritized based on their computed $RI$ values; the results are presented in Figure 5.

It is noteworthy that the result of the risk evaluation and prioritization mechanism will be varied in different cases. In this particular illustrative example, the dominance of risks in the physical flow group as the most critical ones are well-observed (70% of the top ten HEs). Specifically, the listed first three risks are:

1. piracy and terrorism (TL7);
2. force majeure (TD8); and
3. port congestion (TD2).

The most crucial information and payment risks appeared at the fourth and fifth place of this list, respectively:

4. shippers hiding cargo information (non-declare) (II5); and
5. unexpected rise in operational costs (PD2).

While the three most significant risks in the information flow come from the “information inaccuracy or incompletion” branch (II5, II2 and II1), the contribution of the “decrease or total loss of payment” in the field of payment risks is well observed (PD2, PD3 and PD6).

The derived prioritization results show that the applied technique is feasible and functional. Thirty-three identified container shipping operational risks were assessed and prioritized without any two of them having the same rank. Based on the prioritized list as Figure 5, the shipping company could facilitate radical decisions to prevent or mitigate identified risks. Additionally, there is a categorization possibility between risk groups, which could be expressed by significant gaps. For example, the 2.611 disparity of $RI$ values between PD3 and TD7 or the 2.1742 gap between TL6 and II3. This differentiation as well suggested a division of the analyzed risks into different groups based on their priorities and $RI$ values which is also beneficial for the decision-making processes.

5.2 Methodology validation

By adjusting input value of the FRBN and observation of the corresponding change of the output value, the variation, as well as its tendency, are recorded to inspect and validate the proposed risk evaluation model. Taking ID1 as a testing object, DoBs of root nodes were...
adjusted. To observe the effects of input changing in the final result, an experiment is carried out by applying absolute DoB in root nodes. There are two application manners of this validation method was applied: consecutive and cumulative. With the consecutive manner, the adjustments were implemented on root nodes individually, and the inputs were reset after each

<table>
<thead>
<tr>
<th>E code</th>
<th>Hazardous events</th>
<th>RI values</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>TL7</td>
<td>Piracy and terrorism</td>
<td>39.7441</td>
<td>1</td>
</tr>
<tr>
<td>TD8</td>
<td>Force majeure</td>
<td>38.9377</td>
<td>2</td>
</tr>
<tr>
<td>TD2</td>
<td>Port congestion</td>
<td>38.3366</td>
<td>3</td>
</tr>
<tr>
<td>II5</td>
<td>Shippers hiding cargo information (non-declare)</td>
<td>37.9621</td>
<td>4</td>
</tr>
<tr>
<td>PD2</td>
<td>Unexpected rise in operational costs</td>
<td>37.7263</td>
<td>5</td>
</tr>
<tr>
<td>TL4</td>
<td>Damage caused by transporting dangerous goods</td>
<td>37.5948</td>
<td>6</td>
</tr>
<tr>
<td>TL2</td>
<td>Maritime accidents</td>
<td>37.5706</td>
<td>7</td>
</tr>
<tr>
<td>TD1</td>
<td>Port strike, unrest or war situation</td>
<td>37.2250</td>
<td>8</td>
</tr>
<tr>
<td>TL3</td>
<td>Damage to containers or cargo in cargo handling operations</td>
<td>36.9469</td>
<td>9</td>
</tr>
<tr>
<td>II2</td>
<td>Information asymmetry/incompleteness</td>
<td>35.9191</td>
<td>10</td>
</tr>
<tr>
<td>II1</td>
<td>Information system insecurity/vulnerability</td>
<td>34.9984</td>
<td>11</td>
</tr>
<tr>
<td>IT1</td>
<td>IT infrastructure deficiencies</td>
<td>34.7824</td>
<td>12</td>
</tr>
<tr>
<td>PD3</td>
<td>Payers’ financial difficulties or bankruptcy</td>
<td>34.3405</td>
<td>13</td>
</tr>
<tr>
<td>TD7</td>
<td>Cargos or ships being detained by authorities</td>
<td>31.7295</td>
<td>14</td>
</tr>
<tr>
<td>ID3</td>
<td>Unexpected delay in documents or formalities</td>
<td>30.8431</td>
<td>15</td>
</tr>
<tr>
<td>PD6</td>
<td>Containers are abandoned at the port of destination</td>
<td>30.6811</td>
<td>16</td>
</tr>
<tr>
<td>TD5</td>
<td>Container shortage</td>
<td>30.6532</td>
<td>17</td>
</tr>
<tr>
<td>TD3</td>
<td>Unexpected port/terminal cargo handling productivity</td>
<td>29.4661</td>
<td>18</td>
</tr>
<tr>
<td>PP1</td>
<td>Payment delay from partners or shippers</td>
<td>29.2564</td>
<td>19</td>
</tr>
<tr>
<td>II4</td>
<td>Extra information inquiries from shippers</td>
<td>28.2916</td>
<td>20</td>
</tr>
<tr>
<td>TL1</td>
<td>Inland traffic accidents and system inefficiencies</td>
<td>28.0504</td>
<td>21</td>
</tr>
<tr>
<td>PD5</td>
<td>Having partners with bad credit</td>
<td>27.8065</td>
<td>22</td>
</tr>
<tr>
<td>ID2</td>
<td>Unpunctuality in information transmittance</td>
<td>27.7507</td>
<td>23</td>
</tr>
<tr>
<td>IT2</td>
<td>Human errors on the IT infrastructures</td>
<td>26.9686</td>
<td>24</td>
</tr>
<tr>
<td>TD6</td>
<td>Inflexibility fleet operation and management</td>
<td>26.1856</td>
<td>25</td>
</tr>
<tr>
<td>PD4</td>
<td>Shippers breaking the contract/reducing the container volume</td>
<td>24.9031</td>
<td>26</td>
</tr>
<tr>
<td>PD1</td>
<td>Exchange rate fluctuation during payment process</td>
<td>24.3703</td>
<td>27</td>
</tr>
<tr>
<td>TL6</td>
<td>Cargo being stolen or tampered</td>
<td>24.0786</td>
<td>28</td>
</tr>
<tr>
<td>II3</td>
<td>Lack of information standardization and compatibility</td>
<td>21.9044</td>
<td>29</td>
</tr>
<tr>
<td>TL5</td>
<td>Damage to reefer containers due to electricity failure</td>
<td>21.4687</td>
<td>30</td>
</tr>
<tr>
<td>TD4</td>
<td>Unexpected slow steaming or behind voyage schedule</td>
<td>19.7039</td>
<td>31</td>
</tr>
<tr>
<td>PP2</td>
<td>Unrealized contract with partners</td>
<td>18.8543</td>
<td>32</td>
</tr>
<tr>
<td>ID1</td>
<td>Difference in communication interface</td>
<td>16.3684</td>
<td>33</td>
</tr>
</tbody>
</table>

**Notes:** No color: Physical risks; Grey: Information risks; Dark: Payment risks
time. On the other hand, the cumulative manner applied no reset after each adjustment of root nodes. The recorded changes in the RI value of ID1 are presented in Figure 6.

From the experiment, it is observable that the increase in both consecutive and cumulative experiment manner resulted in relatively raises of the final RI value. For instance, put a 100 per cent DoB on the “high” state in the operational impacts node increased the RI value of ID1 by 9.7002. It seems that by the direct causal relationship, the boosting effect is strongest with the adjustment in the Likelihood of Occurrence (29.3949). It could be concluded that the proposed model satisfied the axiom 1. Moreover, in the cumulative adjustments, the continuous growth of the RI values in the absolute DoBs application process proved that the axiom 2 is passed. In fact, the final rise to 100 per cent high DoB of Likelihood of Occurrence caused a surge to reach the 100 RI value of ID1 (16.3684 + 83.6316 = 100). Considering the axiom 3, risk parameters are all have theoretically positive correlations with risk level, and all the executed adjustments showed that they behaved as expected (the rise of the inputs resulted in the positive growth of the RI values). Finally, the proposed model passed the validation process, proved its feasibility and reliability by satisfying all three projected axioms.

6. Conclusion
This study put emphasis on operational risks identification and prioritization in container shipping from the perspective of logistics to reveal potential HEs in the pattern of containerization process and logistics network development. To prevent terminological misunderstandings or ontological misinterpretations, a clear and well-reasoned risk concept was used as the theoretical foundation for identification of existing typical HEs in container shipping operations. To overcome the deficiencies in the utilization of intersubjective assessments on excessively general or complicated problem, an improved two-level of FMEA risk model was constructed including three level 1 parameters (likelihood of occurrence severity of consequence and level of detection) and five level 2 parameters as presented in Figure 2.

Consequently, an FRBN model with a belief structure was built up, highlighted the treatment of the uncertainty in the identified CSORs through multiple supporting solutions. While expressing the extent of risks through a causal network model is a characteristic feature of FRBN, a more specific and tailor-made parameter structure reduces the vagueness
and over-generalization in giving cognitive assessments, which is one of the main causes of epistemic uncertainty. The outcome uncertainty is handled in this model by the fuzzy rules base which expanded the coverage of the model, both parameters and risk level, to any scale through three clearly predefined states (low, medium and high). By applying the proposed model, the identified HEs could be prioritized to facilitate appropriate risk-counter methods. The feasibility of the newly developed method has been proved by the illustrative example of analyzing the risks in container shipping operation. The reliability of technique was also justified through a scientific process using the sensitivity analysis. The results derived by using this technique could be useful for the risk mitigation/prevention or related decision-making processes of container shipping organizations.

For example, it could be well-observed that the derived results in Figure 5 assert a serious concern about the safety and integrity of the physical status of the container fleet with the top three are:

1. piracy and terrorism;
2. force majeure; and
3. port congestion.

In this case, the container shipping company could consider different insurance plans or packages with dissimilar conditions and terms. Figure 7 described a list of such insurance packages. However, the recent contracts with a domestic insurance enterprise indicated that the current plan is the total loss only (TLO) option. Although the insurance fee could be minimized, the fleet of the company is exposed to significant risks of maritime collisions and piracy or terrorism. The suggested risk mitigation manner, in this case, could be changing insurance option from TLO to free of damage absolutely (FOD) or free from particular average (FPA). Another recommended option is a classification of insurance needs. For instance, valuable or detected as perilous voyages should be covered by better insurance packages.

Obviously, it is theoretically possible to apply this FRBN model on a larger scale than a company (e.g. local, national, regional or even industrial). However, it is undeniable that every shipping company has its situation of risk – risk specificity. First, the technical, financial and managerial statuses certainly vary from one company to another. Each company has its specific fleet, infrastructures, key markets and industrial standing that will never be the same as others. They also have dissimilar policies of marketing, customer relation and insurance. Second, the perspectives toward risks and the concepts of states to evaluate it (specifications of low, medium or high) are also dramatically different among companies. Rigidly apply the mechanism to investigate risks in an excessively large scale will not only affect its accuracy as a risk evaluation technique but also make the results of the prioritizing process meaningless. It is therefore recommended that this model should be best applied on an organizational scale.

<table>
<thead>
<tr>
<th>Institute Time Clause (ITC)</th>
<th>Free from Particular Average (FPA)</th>
<th>Total Loss Only (TLO)</th>
<th>Total Loss; Constructive Total Loss; Salvage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free of Damage Absolutely (FOD)</td>
<td>Sue and Labor; Collision Liability; General Average (GA)</td>
<td>Partial losses caused by GA acts but limited to specific components</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Partial losses and Particular Average (PA) caused by firefighting acts or collision</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Partial losses caused by GA acts</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Partial losses and PA</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7. An example of different insurance packages
Meanwhile, some concerns with potentials for further improvements have been identified. First, the weakness of knowledge base, which could be observed in difficulties or ignorance of experts in giving assessment is still not expressed mechanically. Several questions could be raised regarding the possibility of the expert in assessing the knowledge basis of their judgments and the mechanism to effectively extract and process the input data rationally. The manner to express and control “confidence” and the existence of measurable thresholds for “acceptable confidence” in assessment activities are worthy consequent research topics that need substantial investigation. Second, a manner by which represent the customizations and expressions of relative importance among factors and experts is still not available in the proposed model. There are possibilities of injecting the vision or strategy of the system managing board into the proposed FRBN for customizations of the fuzzy rules or a weighing system for the judgments provided by the assessing committee. However, modifications of the model should be based on a reasonable theoretical foundation. Should the model follow the aggregated mental model of subjective perceptions? If the answer is No, then the factors affecting this aspect should be clarified before any customization. Undoubtedly, unsuitable or arbitrary modifications will negatively affect the reliability and effectiveness of the risk quantitative model. These missing pieces could be scrutinized and supplemented by future research to enhance the risk evaluation performance.

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Corresponding author
Son Nguyen can be contacted at: sonng.kt@vimaru.edu.vn

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