MABR
3,2

112

Received 9 January 2018
Accepted 7 February 2018

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

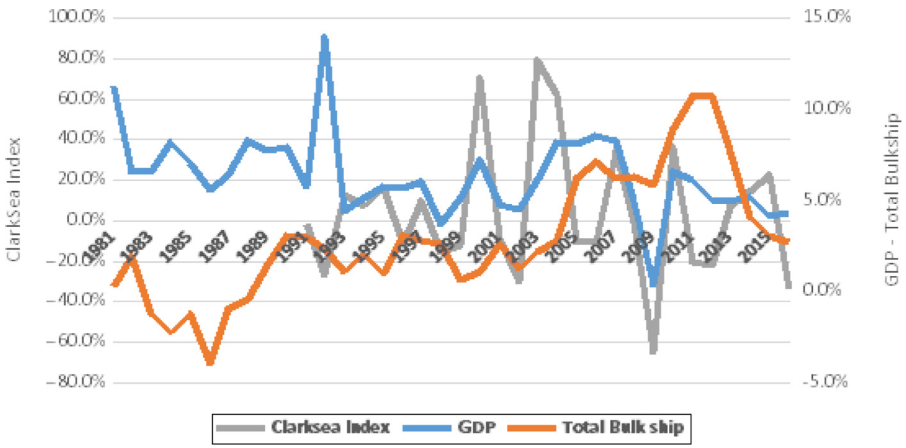
Starting from the works of Charemza and Gronicki (1981) and Sletmo (1989), several scholars underlined how the shipping industry (and shipbuilding) has been characterised by cyclical trends, normally discussed as simply connected to the economic cycle. Beenstock and Vergottis (1989a, 1989b) modelled 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).

Maritime Business Review
Vol. 3 No. 2, 2018
pp. 112-127
Emerald Publishing Limited
2397-3757
DOI 10.1108/MABR-01-2018-0002

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



Source: Own elaboration for Clarkson Database and OECD (2016)

Figure 1.
Maritime trends

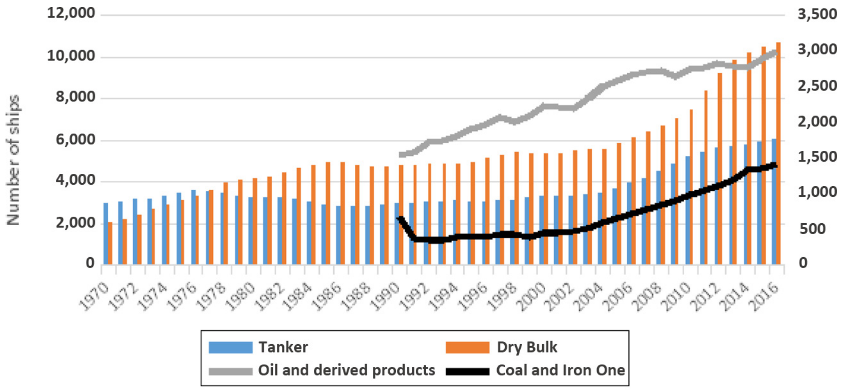
main information channels (Tradewinds, 2016), often the degree of vertical integration of many shipyards – and their importance for the local economy – pushed national authorities to guarantee the survival of these operators, despite adverse market conditions. The importance of the link between shipbuilding 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

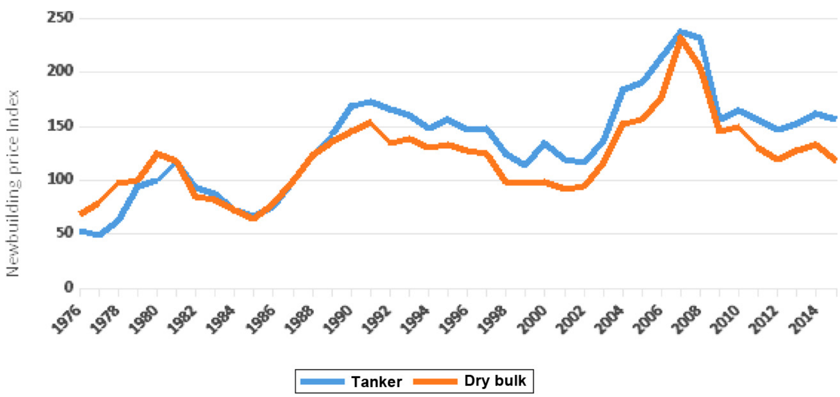


Source: Own elaboration for Clarkson Database (2016)

Figure 2.
Fleet development and trend of main transported cargo

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.



Source: Own elaboration for Clarkson Database (2016)

Figure 3.
Newbuilding price index

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

Variable	Mean	Median	Minimum	Maximum	SD	Skewness	Kurtosis
DFD	5,370.6	4,920	3,293	10,479	1,752.58	1.413	4.376
TFD	3,662.275	3,278.5	2,813	5,886	934.287	1.368	3.438
DNPI	121.30	123.47	64.195	232.14	35.885	0.884	4.206
TNPI	135.162	144.236	49.373	237.187	45.651	0.078	2.547
DSHPI	102.854	94.043	11.069	462.177	85.812	1.993	8.257
TSHPI	93.256	98.783	15.456	241.332	59.884	0.456	2.785
TDD	141.55	104	11	590	138.53	1.344	1.199
TTD	112.64	100	24	277	65.874	0.723	1.363
WSIO	665.189	479.476	344.652	1,363.08	328.698	0.874	2.235
WSOP	649.213	545.217	374.63	1,022.34	212.345	0.347	1.652
DON	1,578	993	344	3,982	1,260.98	0.719	2.095
TON	891	755	232	2,089	551.464	0.844	2.718
ΔGDP	0.756	0.740	−2.27	2.43	0.591	−0.884	7.519
SPI	88.071	83.759	60.54	151.33	22.189	1.058	0.557

Table I.
Descriptive statistic

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.

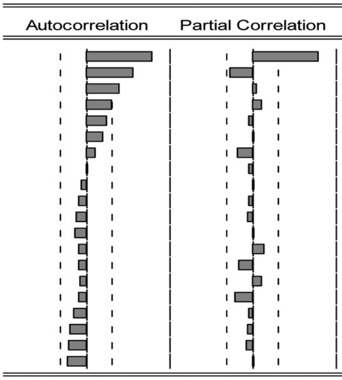
We test the stationarity of all the variables with the augmented Dickey–Fuller and Phillips–Perron tests, and for most of the variables, we cannot reject the null hypothesis of a unit root, which indicates significant evidences of non-stationarity. The GDP quarterly data are already differenced and appear 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.

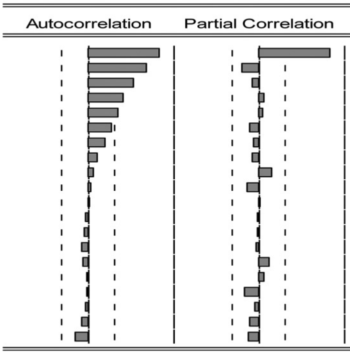
4. Econometric methodology

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:

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



	AC	PAC	Q-Stat	Prob
1	0.827	0.827	29.449	0.000
2	0.597	-0.273	45.216	0.000
3	0.417	0.050	53.125	0.000
4	0.323	0.109	58.009	0.000
5	0.261	-0.039	61.286	0.000
6	0.210	0.005	63.471	0.000
7	0.111	-0.183	64.097	0.000
8	0.003	-0.039	64.097	0.000
9	-0.065	0.032	64.325	0.000
10	-0.097	-0.048	64.848	0.000
11	-0.123	-0.053	65.722	0.000
12	-0.133	0.029	66.784	0.000
13	-0.094	0.149	67.336	0.000
14	-0.087	-0.156	67.823	0.000
15	-0.066	0.107	68.116	0.000
16	-0.097	-0.212	68.774	0.000
17	-0.146	-0.034	70.328	0.000
18	-0.198	-0.057	73.312	0.000
19	-0.217	-0.080	77.083	0.000
20	-0.222	0.008	81.231	0.000



	AC	PAC	Q-Stat	Prob
1	0.871	0.871	32.643	0.000
2	0.712	-0.190	55.043	0.000
3	0.553	-0.080	68.949	0.000
4	0.438	0.081	77.896	0.000
5	0.362	0.050	84.170	0.000
6	0.285	-0.099	88.180	0.000
7	0.206	-0.056	90.334	0.000
8	0.116	-0.075	91.043	0.000
9	0.079	0.167	91.383	0.000
10	0.038	-0.128	91.462	0.000
11	0.011	0.002	91.470	0.000
12	-0.017	-0.015	91.487	0.000
13	-0.047	-0.011	91.625	0.000
14	-0.070	-0.030	91.946	0.000
15	-0.056	0.137	92.160	0.000
16	-0.011	0.066	92.169	0.000
17	-0.008	-0.172	92.174	0.000
18	-0.022	-0.048	92.211	0.000
19	-0.078	-0.099	92.693	0.000
20	-0.150	-0.121	94.582	0.000

Note: Top is dry carrier production variations, bottom is tanker production variations

Figure 4.
Correlograms

where ΔFD_t captures the annual variation in dry bulk carrier or tanker production from time $t-1$ to t, ρ is the autoregressive first-order coefficient and $\boldsymbol{x}_t$ is the vector of all the control variables discussed in the previous section, with parameter vector $\boldsymbol{\alpha}$. 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 observable variable. In Markov switching autoregressive (MS-AR) models *à la* Hamilton (1989), the transition between states depends on a 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:

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

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

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 $d \in [1, \overline{d}]$ is the discrete delay parameter. Equations (1) and (2) can be more compactly represented as:

$$\Delta FD_t = \left(\theta^{(1)}z_t\right)I(\Delta GDP_{t-d} \leq \gamma) + \left(\theta^{(2)}z_t\right)I(\Delta GDP_{t-d} > \gamma) + \varepsilon_t \tag{3}$$

where $I(\cdot)$is the indicator function and z_t is the vector of all the explanatory variables for ΔFD at time t, i.e $z_t = \left(1, \Delta FD_{t-1}, \Delta GDP_t, \Delta GDP_{t-1}, \Delta GDP_{t-2}, \mathrm{x}'_t\right)'$. We denote by $\boldsymbol{\theta}^{(j)}$ the vector of all the regression equation parameters for Regime j, i.e. $\theta^{(j)} = \left(\beta_0^{(j)}, \rho^{(j)}, \beta_1^{(j)}, \beta_2^{(j)}, \alpha^{(j)'}\right)'$, $j = 1, 2$. The errors are assumed to be a Martingale difference series with respect to the past history of ΔPB_t. The parameters of interest are the coefficients $\boldsymbol{\theta} = (\boldsymbol{\theta}^{(1)}, \boldsymbol{\theta}^{(2)})'$, the threshold parameter γ 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 $\gamma \varepsilon \Gamma$, where the elements of Γ 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 Γ).

For any given value of d and γ, the OLS estimate of $\boldsymbol{\theta}$ is computed as:

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

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

For each value of d, we find the estimates of γ as:

$$\hat{\gamma}(d) = \min_{\gamma\in\Gamma}\hat{\sigma}^2\left(\gamma(d)\right)$$

and compute the second-stage estimates of the coefficients as $\hat{\theta}(d) = \hat{\theta}\left(\hat{\gamma}(d)\right)$ and their sample variance as $\check{\sigma}^2(d) = T^{-1}\sum_{t=1}^{T}\check{e}_t(d)^2$ with $\check{e}_t(d) = \left(\Delta PB_t - z'_t\left(\hat{\gamma}(d)\right)\hat{}\left(\hat{\gamma}(d)\right)\right)$. Finally the LS estimate of d are found as:

$$\hat{d}_{LS} = \min_{d\in\left[\underline{d},\overline{d}\right]}\check{\sigma}^2(d)$$

and the LS estimates of γ and the coefficients as $\hat{\gamma}_{LS} = \hat{\gamma}\left(\hat{d}_{LS}\right)$ and $\hat{\boldsymbol{\theta}}_{LS} = \hat{\boldsymbol{\theta}}(\hat{\gamma}_{LS})$. The minimization problem is solved by a direct search over $n\overline{d}$ 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. $\boldsymbol{H_0}{:}\boldsymbol{\theta}^{(1)} = \boldsymbol{\theta}^{(2)}$. 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 γ are not identified. If d and γ were known, the statistic:

$$F_T = sup_{\gamma,d}F_T(\gamma, d)$$

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

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

where $\tilde{\sigma}^2$ 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 γ 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_t^* and define $y_t^* = u_t^*$. Then y_t^* is regressed on the one-stage explanatory variables to obtain$\tilde{\sigma}^{*2}$, and on the two-stage explanatory variables to obtain $\hat{\sigma}^{*2}(\gamma, d)$ and form:

$$F_T^*(\gamma) = T\left(\frac{\tilde{\sigma}^{*2} - \hat{\sigma}^{*2}(\gamma, d)}{\hat{\sigma}^{*2}(\gamma, d)}\right)$$

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 $\boldsymbol{\theta}$. 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 tests are 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 one 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

Model	(1)	(3)
Regime 1		
Constant	0.013**	0.026*
ΔBP_{t-1}	0.761**	0.642***
ΔGDP_t	0.011	0.015
ΔGDP_{t-1}	0.531**	0.287**
ΔGDP_{t-2}	0.485**	0.239**
$\Delta BNPI_t$	−0.012	−0.034
$\Delta BNPI_{t-1}$	−0.201**	−0.098**
$\Delta BNPI_{t-2}$	−0.035**	−0.168**
ΔSPI_{t-1}	−0.067*	−0.071**
ΔSPI_{t-2}	−0.126**	−0.096***
$\Delta BSHPI_t$	0.081*	0.099*
ΔTBD_t	−0.005	−0.030
ΔTBD_{t-1}	−0.021*	−0.056*
$\Delta WSIO_t$	0.023*	0.018
$\Delta WSIO_{t-1}$	0.612**	0.154**
$\Delta WSIO_{t-2}$	0.076***	0.197**
ΔBON_t	−0.012	−0.017
ΔBON_{t-1}	−0.207*	−0.133*
Regime 2		
Constant		0.076*
ΔBFD_{t-1}		0.774***
ΔGDP_t		0.034
ΔGDP_{t-1}		0.326***
ΔGDP_{t-2}		0.462***
$\Delta BNPI_t$		−0.041
$\Delta BNPI_{t-1}$		−0.167**
$\Delta BNPI_{t-2}$		−0.182**
ΔSPI_{t-1}		−0.098**
ΔSPI_{t-2}		−0.101**
$\Delta BSHPI_t$		0.036
ΔTBD_t		−0.002
ΔTBD_{t-1}		−0.093**
$\Delta WSIOT_t$		0.011
$\Delta WSIOT_{t-1}$		0.196***
$\Delta WSIOT_{t-2}$		0.231***
ΔBON_t		−0.056
ΔBON_{t-1}		−0.261*
γ	NA	0.33**
d		1.000
Adjusted R^2	0.116	0.853
LR test	NA	44.35***
p value		0.0000
N_1	NA	17
N_2	NA	23
$\eta\%$		0.15
No. of bootstraps		1000
$Q_m(10)$	9.765 (0.665)	7.342 (0.324)
ARCH(10)	15.653 (0.876)	11.541 (0.546)

Notes: [a]This table presents the conditional LS estimates for the one- and two-stage models for dry bulk carriers and tankers. γ 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 *Qm(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[a]

Model	(1)	(3)
Regime 1		
Constant	0.016**	0.021*
ΔTFD_{t-1}	0.481***	0.592***
ΔGDP_t	0.013	0.016
ΔGDP_{t-1}	0.278**	0.2031**
ΔGDP_{t-2}	0.301**	0.178**
$\Delta TNPI_t$	0.008	0.031
$\Delta TNPI_{t-1}$	−0.198**	−0.082**
$\Delta TNPI_{t-2}$	−0.029**	−0.056*
ΔSPI_{t-1}	−0.017**	−0.052**
ΔSPI_{t-2}	−0.046**	−0.086**
$\Delta TSHPI_t$	0.073*	0.027
ΔTTD_t	−0.005	−0.006
ΔTTD_{t-1}	−0.011*	−0.058**
$\Delta WSOT_t$	0.031*	0.017
$\Delta WSOT_{t-1}$	0.571***	0.072***
$\Delta WSOT_{t-2}$	0.101***	0.113***
ΔTON_t	−0.009	−0.011
ΔTON_{t-1}	−0.201*	−0.128**
Regime 2		
constant		0.0183**
ΔTFD_{t-1}		0.771**
ΔGDP_t		0.007
ΔGDP_{t-1}		0.679**
ΔGDP_{t-2}		0.578***
$\Delta TNPI_t$		0.531*
$\Delta TNPI_{t-1}$		−0.321**
$\Delta TNPI_{t-2}$		−0.376***
ΔSPI_{t-1}		−0.125***
ΔSPI_{t-2}		−0.183***
$\Delta TSHPI_t$		0.085*
ΔTTD_t		−0.046
ΔTTD_{t-1}		−0.187*
$\Delta WSOT_t$		0.013
$\Delta WSOT_{t-1}$		0.165**
$\Delta WSOT_{t-2}$		0.231***
ΔTON_t		−0.032
ΔTON_{t-1}		−0.254**
γ	NA	0.31***
d		1.001
R^2	0.138	0.837
LR test		53.78***
p value		0.000
N_1		21
N_2		19
η%		0.15
No. of bootstrap		1000
$Q_m(10)$	7.987 (0.664)	5.638 (0.337)
ARCH(10)	13.256 (0.654)	9.876 (0.232)

Notes: [a]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, 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 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

Table III.
Estimates for the Regime 1 and Regime 2 threshold models for liquid bulksa

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.

References

Audia, P.G. and Greve, H.R. (2006), "Less likely to fail: low performance, firm size, and factory expansion in the shipbuilding industry", *Management Science*, Vol. 52 No. 1, pp. 83-94.

Beenstock, M. and Vergottis, A. (1989a), "An econometric model of the world tanker market", *Journal of Transport Economics and Policy*, Vol. 23 No. 3, pp. 263-280.

Beenstock, M. and Vergottis, A. (1989b), "An econometric model of the world market for dry cargo freight and shipping", *Applied Economics*, Vol. 21 No. 3, pp. 339-356.

Bijwaard, G. and Knapp, S. (2009), "Analysis of ship life cycles – the impact of economic cycles and ship inspections", *Marine Policy*, Vol. 33 No. 2, pp. 350-369.

Charemza, W. and Gronicki, M. (1981), "An econometric model of world shipping and shipbuilding", *Maritime Policy & Management*, Vol. 8 No. 1, pp. 21-30.

Grigorut, C., Nistor, F. and Popa, C. (2013), "Crisis effects on shipbuilding market", *Ovidius University Annals, Series Economic Sciences*, Vol. 13 No. 2, pp. 31-34.

Guerrero, D. and Rodrigue, J.P. (2014), "The waves of containerization: shifts in global Maritime transportation", *Journal of Transport Geography*, Vol. 34, pp. 151-164.

Hamilton, J.D. (1989), "A new approach to the economic analysis of nonstationary time series and the business cycle", *Econometrica*, Vol. 57 No. 2, pp. 357-384.

Hansen, B.E. (1996), "Inference when a nuisance parameter is not identified under the null hypothesis", *Econometrica*, Vol. 64 No. 2, pp. 413-430.

Hansen, B.E. (1997), "Inference in TAR models", *Non-Linear Dynamics and Econometrics*, Vol. 2 No. 1, pp. 1-14.

Klovland, J. (2002), "Business cycle, commodity prices, and shipping freight rates: some evidence from the pre-WWI period, *SNF report 48*, Institute for research on economics and business administration, Bergen.

Knapp, S., Kumar, S.N. and Remijn, A.R. (2008), "Econometric analysis of the ship demolition market", *Marine Policy*, Vol. 32 No. 6, pp. 1023-1036.

Li, C.W. and Li, W.K. (1996), "On a double-threshold autoregressive heteroscedastic time series model", *Journal of Applied Econometrics*, Vol. 11 No. 3, pp. 253-274.

Li, W.K. and Mak, T.K. (1994), "On the squared residual autocorrelations in non-linear time series with conditional heteroscedasticity", *Journal of Time Series Analysis*, Vol. 15 No. 6, pp. 627-636.

Potter, S.M. (1995), "A non-linear approach to US GDP", *Journal of Applied Econometrics*, Vol. 10 No. 2, pp. 109-125.

Robinson, P.M. (1995), "Gaussian semiparametric estimation of long range dependence", *The Annals of Statistics*, Vol. 23 No. 5, pp. 1630-1661.

Scarsi, R. (2007), "The bulk shipping business: market cycles and Shipowners' biases", *Maritime Policy & Management*, Vol. 34 No. 6, pp. 577-590.

Shin, D.H. and Hassink, R. (2011), "Cluster life cycles: the case of the shipbuilding industry cluster in South Korea", *Regional Studies*, Vol. 45 No. 10, pp. 1387-1402.

Sletmo, G. (1989), "Shipping's fourth wave: ship management and Vernon's trade cycles", *Maritime Policy & Management*, Vol. 16 No. 4, pp. 293-303.

Solesvik, M. (2016), "Innovation strategies in shipbuilding: the shipbuilding cycle perspective", *Shipbuilding and Marine Infrastructure*, Vol. 5 Nos 1/2, pp. 44-50.

Stopford, M. (1987), "A new life for shipbuilding in the 1990s?", *Maritime Policy & Management*, Vol. 14 No. 4, pp. 301-312.

Stopford, M. (2009), *Maritime Economics*, 3rd Ed., Routledge, London.

Stopford, M. and Barton, J. (1986), "Economic problems of shipbuilding and the state", *Maritime Policy & Management*, Vol. 13 No. 1, pp. 27-44.

Stott, P.W. (2017), "Shipbuilding innovation: enabling technologies and economic imperatives", *Journal of Ship Production and Design*, Vol. 33 No. 3, pp. 1-11.

Tiao, G.C. and Tsay, R.S. (1991), "Some advances in non-linear and adaptive modelling in time series", *Journal of Forecasting*, Vol. 13 No. 2, pp. 109-131.

Tong, H. (1986), "On estimating thresholds in autoregressive models", *Journal of Time Series Analysis*, Vol. 7 No. 3, pp. 179-190.

Tong, H. (1990), *Non-Linear Time Series: A Dynamical System Approach*, Oxford University Press, Oxford.

Tradewinds (2016), available at: www.tradewindsnews.com/

Van Klink, A. and de Langen, P. (2001), "Cycles in industrial clusters: the case of the shipbuilding industry in the Northern Netherlands", *Economische En Social Geografie*, Vol. 92 No. 4, pp. 449-463.

Volk, B. (1994), *The Shipbuilding Cycle – A Phenomenon Explained*, Institute of Shipping Economics and Logistics, Bremen.

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