Shipbuilding and economic cycles: insights from a non-linear econometric model

Claudio Ferrari – University of Genoa
Malvina Marchese – University of Genoa
Alessio Tei – Newcastle University[1]

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 influenced both the trade patterns and the 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 goal of this paper is then 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 the shipbuilding and the economic cycles over the last 30 years. The research focuses on identifying the cycle characteristics and understanding the asymmetric 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: *Shipbuilding cycles, Fleet development, Shipping market, Bulk shipping*

Article Classification: *Research Paper*

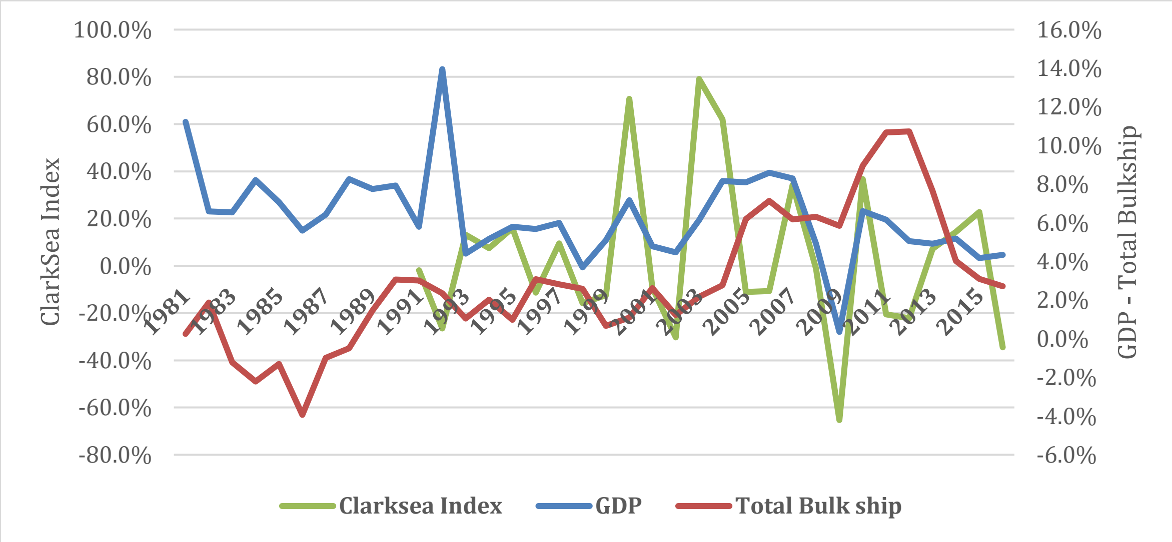
[1] Corresponding author. Mail: alessio.tei@ncl.ac.uk

1. Introduction

Starting from the works of Charezma 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 all the main maritime economics textbooks (e.g. Stopford, 2009) – influences main developments in the shipping industry determining a series of effects in operators' strategies (e.g. Scarsi, 2007) and in the ship's life (e.g. 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 theory) 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 container industry and its geographical diffusion linked to the macroeconomic trend. Yet they underlined how the long-term cycle in maritime industry should always be linked to short term effects that influence 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 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 '80s 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.

Figure 1 – Maritime trends



Source: own elaboration for Clarkson Database and OECD, 2016.

Several authors (e.g. 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 (e.g. Shin and Hassink, 2011; Van Klink and de Langen, 2001; Stopford, 1987; Stopford and Barton, 1986) and industry reports, shipbuilding industry is heavily dependent from 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 big market operators, affecting the overall debt level and the probability to fail. As recently noted by main information channels (e.g. 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.

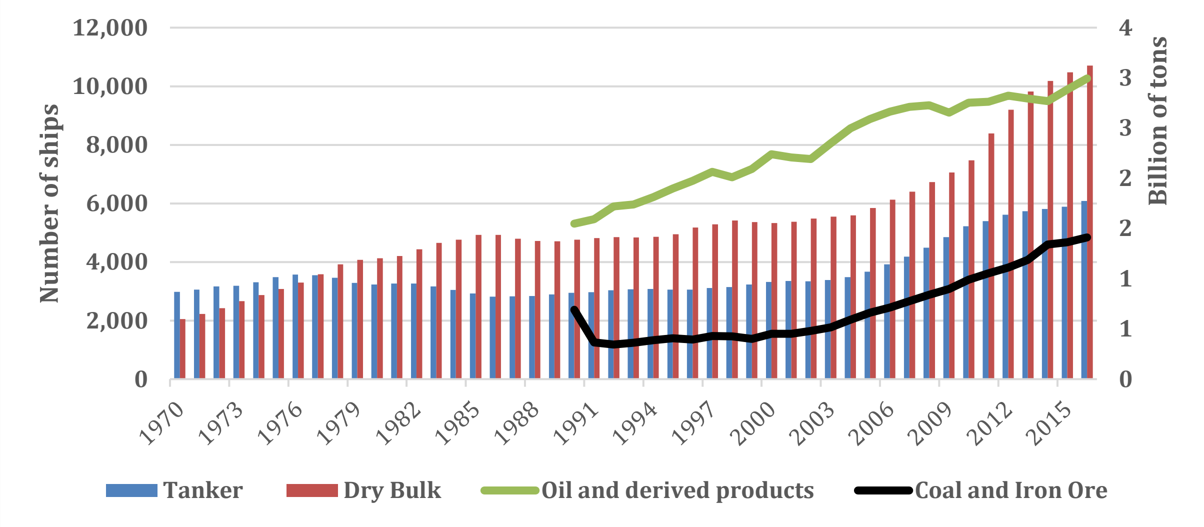
Despite the importance of the abovementioned topic, several studies discussed the shipbuilding cycle but few of them tried to apply econometrics techniques in order to understand the effects of main economic and shipping related trends on the shipbuilding industry. The current study tries to fill this gap, using a novel approach in order 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 in order 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 discusses 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 the changing market conditions. Thus, the shipbuilding market is characterised by high rigidity that makes market trends fundamental in order 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% generating drastic effects on the market that – as underlined by Solesvik (2016) – can only be mitigated through public intervention and, recently, to the 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 homogenous sector, different subsectors can be identified. Thus, even in negative periods, different market niches register positive trends (e.g. cruise, offshore support vessels). Despite this consideration, 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 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.

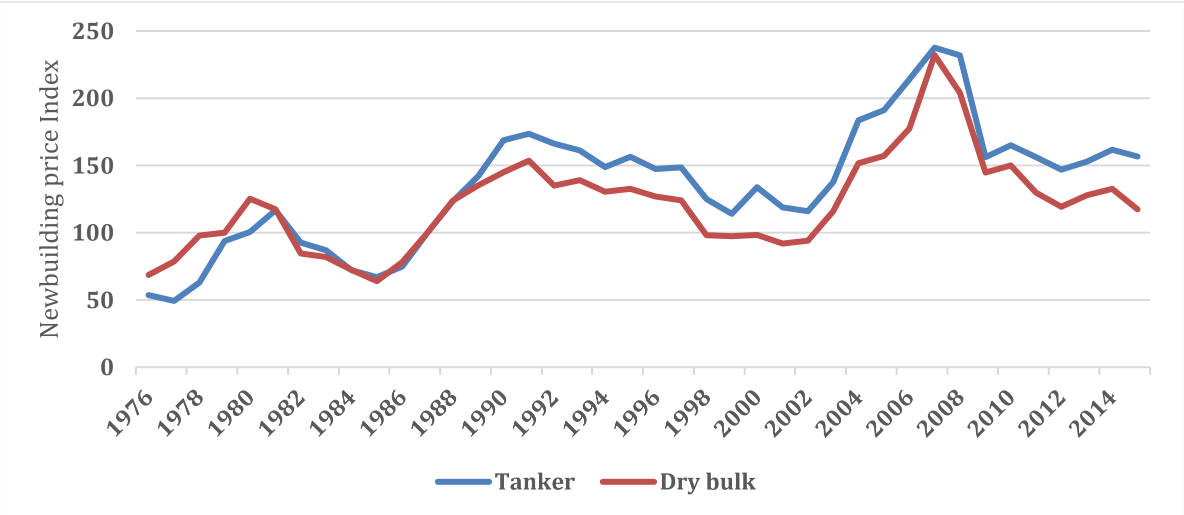
Figure 2 – Fleet development and trend of main transported cargo



Source: own elaboration for Clarkson Database, 2016.

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 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, generate the current shipbuilding situation.

Figure 3 – Newbuilding price index



Source: own elaboration for Clarkson Database, 2016.

2.1. Data collection

The abovementioned scenario leads to the necessity to better understand the shipbuilding market evolution in order to plan in a more sustainable way the strategic development of the related markets. Moreover, as noted for other sectors, different cycle phases can register a diversified effect (i.e. magnitude) by main elements that traditionally affect the industry.

In order to identify the cyclical patterns, we collected various explanatory variables mainly through public available sources (e.g. OECD) and specialised database (e.g. Clarkson). Our research focuses on the two main shipbuilding sectors that are currently facing a situation of major crisis (i.e. dry and liquid bulk). In order to perform the analysis, annual data from the '70s have been collected but – given the necessity to collect different kinds of information for the two represented markets – the complete dataset include 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 helped us in 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. 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 for the liquid bulk [WSOP]). Concerning business related variables, shipbuilding price, demolitions, and overall saturation of the shipyards have been used as main variables. In particular, new shipbuilding prices [DNPI and TNPI depending on the reference market] and second hand ship building prices [DSHPI and TSHPI] will represent main business monetary elements that are traditionally linked to the strategic choice to buy 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 ship's life cycle. Normally demolitions are planned in phases of crisis (or to solve overcapacity issues) while they are postpone in time 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) since 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. Since the decision of purchasing a ship is normally made months (and sometime years) in advance of actual ship delivery, a lag of some decisional variable is added – using a proper estimation technique to assess it – in order to individuate also the lag in decision making process that affect the overall shipbuilding market.

3. Dataset

Our data set consists of a time series of annual observations spanning from 1986 until 2015. To identify economic cycles we use quarterly observations on GDP growth per capita from the first quarter of 1976 to the fourth quarter 2015. Descriptive statistics for our variables are reported in Table 1.

Table 1 - descriptive statistic

Variable	Mean	Median	Minimum	Maximum	Standard deviation	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

The distributions of dry-bulk fleet development and tanker fleet development are skewed to the right and are fatter tailed than the Gaussian distribution. The Jarque-Brera test indicates for both variables rejection of the Normality assumption, with p-values of 0.00167 and 0.001659 respectively for dry bulk carriers and tankers. 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 is already differenced and appears 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).

Figure 4 - Correlograms (top is dry carrier production variations, bottom is tanker production variations)

Autocorrelation	Partial Correlation		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

Autocorrelation	Partial Correlation		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

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. The econometric methodology

Our starting hypothesis is that the variation in bulk carrier production is affected by the economic cycle and such 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 one regime dynamic lag model:

$$\Delta FD_t = \beta_0 + \rho \Delta FD_{t-1} + \beta_1 \Delta GDP_t + \beta_2 \Delta GDP_{t-1} + \beta_3 \Delta GDP_{t-2} + \boldsymbol{\alpha}' \boldsymbol{x}_t + u_t, \quad (1)$$

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. that 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 shipping production which might hinder important characteristic of the shipping cycles (e.g. Charezma and Gronicki, 1981).

In recent years there has been considerable interest 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 *a' la* Hamilton (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) *a' 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. Since we want to analyse whether the impact of GDP fluctuations on the shipping cycles is significant and different across business cycle phases, our threshold variable is an observable business cycle indicator and we employ a TAR model. This methodology allows us 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:

$$\Delta FD_t = \beta_0^{(1)} + \rho^{(1)}\Delta BFD_{t-1} + \beta_1^{(1)}\Delta GDP_t + \beta_2^{(1)}\Delta GDP_{t-1} + \beta_3^{(1)}\Delta GDP_{t-2} + \boldsymbol{\alpha}^{(1)}\boldsymbol{x}_t + \varepsilon_t \quad \Delta GDP_{t-d} \leq \gamma \qquad \textit{(2a)}$$

$$\Delta FD_t = \beta_0^{(2)} + \rho^{(2)}\Delta BFD_{t-1} + \beta_1^{(2)}\Delta GDP_t + \beta_2^{(2)}\Delta GDP_{t-1} + \beta_3^{(2)}\Delta GDP_{t-2} + \boldsymbol{\alpha}^{(2)}\boldsymbol{x}_t + \varepsilon_t \quad \Delta GDP_{t-d} > \gamma \qquad \textit{(2b)}$$

The model is piecewise linear and it allows all the regression parameters to change depending on the value of the threshold variable. Here we characterize each regime 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 $d \in [1, \bar{d}]$ is the discrete delay parameter. Equations (1) and (2) can be more compactly represented as:

$$\Delta FD_t = \left(\boldsymbol{\theta}^{(1)}\boldsymbol{z}_t\right) I(\Delta GDP_{t-d} \leq \gamma) + \left(\boldsymbol{\theta}^{(2)}\boldsymbol{z}_t\right) I(\Delta GDP_{t-d} > \gamma) + \varepsilon_t \qquad \textit{(3)}$$

where $I(\cdot)$ is the indicator function and $\boldsymbol{z}_t$ is the vector of all the explanatory variables for ΔFD at time t, i.e $\boldsymbol{z}_t = (1, \Delta FD_{t-1}, \Delta GDP_t, \Delta GDP_{t-1}, \Delta GDP_{t-2}, \boldsymbol{x}'_t)'$. We denote by $\boldsymbol{\theta}^{(j)}$ the vector of all the regression equation parameters for regime j, i.e. $\boldsymbol{\theta}^{(j)} = (\beta_0^{(j)}, \rho^{(j)}, \beta_1^{(j)}, \beta_2^{(j)}, \boldsymbol{\alpha}^{(j)\prime})'$, $j = 1,2$. 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. Since 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. Since 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 Γ are less than T because we must take a certain percentage ($\eta\%$) of observations to ensure a minimum number of them in each regime (henceforth let n denote the number of elements in Γ).

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

$$\widehat{\boldsymbol{\theta}}(\gamma(d)) = \left(\sum_{t=1}^{T} \boldsymbol{z}_t\big(\gamma(d)\big)\, \boldsymbol{z}'_t(\gamma(d))\right)^{-1} \left(\sum_{t=1}^{T} \boldsymbol{z}_t\big(\gamma(d)\big)\, \boldsymbol{z}'_t(\gamma(d))\right)$$

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 $\hat{e}_t(\gamma(d)) = (\Delta PB_t - \boldsymbol{z}'_t(\gamma(d))\widehat{\boldsymbol{\theta}}(\gamma(d)))$.

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

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

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

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

and the LS estimates of γ and the coefficients as $\hat{\gamma}_{LS} = \hat{\gamma}(\hat{d}_{LS})$ and $\widehat{\boldsymbol{\theta}}_{LS} = \widehat{\boldsymbol{\theta}}(\hat{\gamma}_{LS})$. The minimization problem is solved by direct search over $n\bar{d}$ regressions.

To verify if our 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 due 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 $\tilde{\sigma}^2$ denotes the residual sum of squares under the null hypothesis, would have near optimal power against alternatives since F_T is a monotonic function in $\hat{\sigma}^2$, the residual sum of squares of the unrestricted model. Since γ and *d* are not identified, the asymptotic distribution of F_T is not a chi-squared. Hansen (1996) shows that the asymptotic distribution can be approximated by a bootstrap procedure. We generate T random draws from a N(0,1) distribution u_t^* and define $y_t^* = u_t^*$. We then regress y_t^* on the one-stage explanatory variables to obtain $\tilde{\sigma}^{*2}$, and on the two-stages 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 2a and 2b report the results for the two estimated models (i.e. the one regime and the two regimes threshold models) estimated respectively for dry (panel 2a) and liquid bulk production (panel 2b) variations. Regime 1 represents captures economic cycles slowdown while regime 2 represents the economic cycle expansion phases.

Table 2a - Estimates for one and two regime threshold models for dry bulk[2]

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

[2] These tables present the conditional LS estimates for the one and two stages 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 number of observations that lie in the first and in the second regime, respectively. LR is the likelihood ratio test for the null of non-threshold whose p-value is computed through bootstrap. N. 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 the one regime model and their extensions by Li and Li (1996) for the two regime models.

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
Adj R^2	0.116	0.853
LR test	NA	44.35***
pvalue		0.0000
N_1	NA	17
N_2	NA	23
η%		0.15
N. of bootstrap		1000
$Q_m(10)$	9.765 (0.665)	7.342 (0.324)
ARCH(10)	15.653 (0.876)	11.541 (0.546)

Table 2b - Estimates for the one and two regime threshold models for liquid bulks

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**
Υ	NA	0.31***
d		1.001
R^2	0.138	0.837
LR test		53.78***
pvalue		0.000
N_1		21
N_2		19
η%		0.15
N. of bootstrap		1000
$Q_m(10)$	7.987 (0.664)	5.638 (0.337)

ARCH(10)	13.256 (0.654)	9.876 (0.232)

The 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 shipbuilding production. Results show that shipbuilding saturation level and 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 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 of serial correlation or time series heteroscedasticity, however their goodness of fit is quite low, with the adjusted R^2 respectively at 0.116 for dry carriers and 0.138 for 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 type 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 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.

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-regimes specification is that it allows endogenous estimation of the threshold that determine the switch between an expansion and a declining phase. As shown in Table 2, the value of the threshold is very similar for dry and liquid bulk carriers, ranging between 0.31% and 0.33%. 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 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, shipbuilding industry tends to avoid strong reductions in terms of production, facilitating the generation of overcapacity. This latter elements could be connected to the impossibility to stop the production facilities in which companies invested during the expansion phase. On this regards, the presence of cluster authorities or the involvement of government agencies (as done in Japan and, recently, in 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 2 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 to estimate signals with different time periods could help shipyards to better evaluate their backlogs or to 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 sector 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 researches 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 elements on the shipbuilding industry varies depending on the related 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 since 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 magnitude in the effects, both studied sectors show similar trends, underlining how shipbuilding sector react 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 in order to use it as prediction tool, calibrating relative results in respect to the different sensitivity of the variables and related cyclical phase.

References

Audia P.G., Greve H.R. (2006). Less Likely to Fail: Low Performance, Firm Size, and Factory Expansion in the Shipbuilding Industry, Management Science, 52, pp. 83-94.

Beenstock M., Vergottis A. (1989a). An econometric model of the world tanker market, Journal of Transport Economics and Policy, 23 pp. 263–280.

Beenstock M., Vergottis A. (1989b). An econometric model of the world market for dry cargo freight and shipping, Applied Economics, 21, pp. 339–356.

Bijwaard G., Knapp S. (2009). Analysis of ship life cycles - The impact of economic cycles and ship inspections, Marine Policy, 33, pp. 350–369.

Charemza W., Gronicki M. (1981). An econometric model of world shipping and shipbuilding, Maritime Policy & Management, 8, pp. 21-30.

Grigorut C., Nistor F., Popa C. (2013). Crisis Effects on Shipbuilding Market, Ovidius University Annals, Series Economic Sciences, 13, pp. 31-34.

Guerrero D., Rodrigue J.P. (2014). The waves of containerization: shifts in global maritime transportation, Journal of Transport Geography, 34, pp. 151–164.

Hamilton J.D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica, 2, pp. 357-384.

Hansen B.E. (1996). Inference When a Nuisance Parameter is Not Identified under the Null Hypothesis. Econometrica, 64, pp. 413-430.

Hansen B.E. (1997). Inference in TAR Models. Non-linear Dynamics and Econometrics, 2, pp. 1-14.

Kim C.J, Piger J.M. (1997). A Markov Switching Model of Business Cycles Dynamics with a Post-recession "bounce-back" Effect, Cambridge University Press.

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., Remijn A.R. (2008). Econometric analysis of the ship demolition market, Marine Policy, 32, pp. 1023–1036.

Li C.W., Li W.K. (1996). On a double-threshold autoregressive heteroscedastic time series model, Journal of Applied Econometrics, 11, pp. 253-274.

Li W.K., Mak T.K. (1994). On the squared residual autocorrelations in non‐linear time series with conditional heteroscedasticity, Journal of Time Series Analysis, 15, pp. 627-636.

Potter S.M. (1995). A Non-Linear Approach to US GDP. Journal of Applied Econometrics, 10, pp. 109-125.

Robinson P.M. (1995). Gaussian Semiparametric Estimation of Long Range Dependence. The Annals of Statistics, 23, pp. 1630-1661.

Scarsi R. (2007). The bulk shipping business: market cycles and shipowners' biases, Maritime Policy & Management, 34, pp. 577-590.

Shin D.H., Hassink R. (2011). Cluster Life Cycles: The Case of the Shipbuilding Industry Cluster in South Korea, Regional Studies, 45, pp. 1387-1402.

Sletmo G. (1989). Shipping's fourth wave: ship management and Vernon's trade cycles, Maritime Policy & Management, 16, pp. 293-303.

Solesvik M. (2016). Innovation strategies in shipbuilding: The shipbuilding cycle perspective, Shipbuilding and Marine Infrastructure, 5, pp. 44-50.

Stopford M. (1987). A new life for shipbuilding in the 1990s?, Maritime Policy & Management, 14, pp. 301-312.

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

Stopford, M., Barton J. (1986). Economic problems of shipbuilding and the state, Maritime Policy & Management, 13, pp. 27-44.

Stott, P.W. (2017). Shipbuilding innovation: enabling technologies and economic imperatives. Journal of Ship Production and Design, 33, pp. 1-11.

Tiao G.C, Tsai R.S. (1991). Some Advances in Non-linear and Adaptive Modelling in Time Series. Journal of forecasting, 13, pp. 109-131.

Tong H. (1990). Non-linear Time Series: a Dynamical System Approach, Oxford University Press.

Tong H. (1986). On Estimating Thresholds in Autoregressive Models, Journal of Time Series Analysis, 7, pp. 179-190.

Tradewinds (2016). http://www.tradewindsnews.com/

Van Klink A., de Langen P. (2001). Cycles in industrial clusters: the case of the shipbuilding industry in the northern Netherlands, Economische en Social Geografie, 92, pp. 449-463.

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