Estimation of newbuilding prices and lead times for bulk carriers using generalized additive models

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Abstract

The shipping market has gone through a rough time since the start of the crisis. Today the general sentiment is that rates are improving and that the worst is behind us. However for the shipbuilding sector this does not seem to hold, with rising market sentiment, more orders would be expected, however, the uncertainty around the required Green House Gas reductions agreed upon by the IMO, seems to withhold ship owners from increasing their number of orders for ships. Therefore, this research focuses on the shipbuilding sector and the impact these new regulations have on it. This paper will focus on the first part of this investigation; the creation of a newbuilding price and lead time models. After consideration of relevant literature, the general additive model (GAM) has been chosen and is applied both to the newbuilding price and the lead time as these two elements are seen to mutually influence each other. For the creation of these models, backward elimination was used resulting in a large number of variables tested and compared for relevance. The final results are promising, though the lead time will require further research to increase explanatory power.

Keywords: *General Additive Model, Shipbuilding, Dry bulk, Maritime Economics, Price estimation, Lead time estimation*

1. Introduction

Shipping is slowly recovering after one of the largest and longest crises in its history. Today rates are improving and at a sustainable level once more. However for the shipbuilding sector, this does not seem to hold, with rising market sentiment, more orders would be expected. However, this is not the case (Steidl et al., 2018). The uncertainty around the required Green House Gas reductions agreed upon by the IMO (2018) may withhold ship owners from ordering large numbers of ships. Similar effects have been studied for the introduction of the EEDI (e.g. Bouman et al. (2017), Zheng et al. (2013) and Pruyn (2017)). Although till now no clear impact was identified. This research, therefore, focuses on the shipbuilding sector and the impact these new regulations have on it, rather than the ships or ship owners. This paper will focus on the first part of this investigation; the creation of a newbuilding price and lead time models. After consideration of relevant literature, the general additive model (GAM) has been chosen and is applied both to the newbuilding price and the lead time as these two elements are seen to mutually influence each other. For the creation of these models backward elimination was used resulting in a large number of variables tested and compared for relevance.

2. Literature Review

The modelling of the ship newbuilding market is not new, the first known one on tankers was by Koopmans (1939) and many have followed since. Looking at the literature on this subject since 2000, it can be noted that Strandenes (2002) discusses the newbuild market, but does not go into a detailed model for it. Dikos (2004) disagrees with Strandenes suggestions and shows that prices are the result of a competitive equilibrium when executing real options under uncertainty. Haralambides et al. (2005) identify the relation between newbuilding prices and secondhand prices to be good substitutes.

Adland et al. (2006) and Adland and Jia (2015) investigate the combination of lead time (time between signing the contract and delivery, called delivery lag by them), newbuilding price and secondhand price, underlining the importance of the variations over time in lead time and their influence on the newbuilding price. The time varying lead time explains to a large extent the difference between volatile secondhand prices and stickier newbuilding prices based on their Vector Error Correction Method. Pruyn (2013) in his thesis applies a Generalized Additive Model (GAM) to both newbuilding and secondhand prices for dry bulk carriers as part of a larger model; besides prices, his focus is on the order book size as a key element of influence, rather than the lead time.

Raju et al. (2016) study the volatility in LNG Vessel newbuilding prices using generalized autoregressive conditional heteroscedastic (GARCH) and exponential generalized autoregressive conditional heteroscedastic (EGARCH) methods. Their main conclusion is that prices are volatile for these vessels, unlike the assumption of stickiness by Adland before. In the last paper on newbuilding prices identified Adland et al. (2017) take a look at this market once more. Now the impact of heterogeneity in owners and yards on prices is investigated, a more detailed study than the earlier papers. Compensated Gross Tonnage (CGT) is used as a value for complexity, though admittedly it does not capture all specific complexity such as cranes, ice-class, different engine configurations, etc.

As has become clear from the review above, only a small number of papers have been devoted to newbuilding prices in the last 20 years. In line with the papers of Adland (Adland et al., 2006, Adland and Jia, 2015, Adland et al., 2017) and the work of Pruyn (2017), this paper will investigate both newbuilding prices and lead time of dry bulk vessels using a Generalized Additive Model (GAM). In addition to the previously mentioned papers, this research will investigate the significance of the technical features of a vessel that potentially increase the price or lead time, as suggested by Adland et al. (2017). The GAM offers both a structure to incorporate this as well as good prediction performance.

3. Generalized Additive Models

GAM is introduced elaborately by Wood (2017), with a general structure as follows:

$$g(\mu_i) = A_i\theta + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}) + ... \tag{1}$$

Where $\mu_i \equiv E(Y_i)$ and $Y_i \sim EF(\mu_i, \varphi)$. Yi is a response (dependent) variable and $EF(\mu_i, \varphi)$ denotes an exponential family of distribution with mean μ_i and scale parameter, φ, A_i is a row of the model matrix for any strictly parametric model components, θ is the corresponding parameter vector, and the f_j are smooth (non-parametric) functions of the covariates, x_k.

GAM has several key assumptions to be aware of:

- The data of the dependent variable are independently distributed, i.e., cases are independent. The dependent variable does not need to be normally distributed, but it typically assumes a distribution from an exponential family (e.g. Poisson, binomial, gamma, normal …).
- Unlike linear regression and GLM, GAM does not assume a linear relationship between the dependent variable and the independent variables, nor a linear relationship between the transformed responses in terms of the link function and the explanatory variables, but it assumes a linear relationship between the independent variable transformed by the link function and the dependent variables transformed by the smooth functions.
- The residuals need to be independent but do not have to be normally distributed, instead they could also follow any form of exponential distribution.
- The residuals should have a mean of zero and their variance should be constant. In other words, the residuals plots should have the same variation for all values of the linear predictors (fitted values).

The presentation and estimation of component functions of a GAM model are best introduced by considering a model containing one function and one covariate, as follows:

$$y_i = f(x_i) + \varepsilon_i \tag{2}$$

Where y_i is a response variable, x_i is a covariate, f is a smooth function and the ε_i are independent $N(0, \sigma^2)$ random errors.

To estimate f requires that f be represented in such a way that equation (2) becomes a linear model. This can be done by choosing some basic functions, defining the space of functions of which f is an element. If $b_j(x)$ is the jth such basis function, for some values of the unknown parameters, f is assumed to have a representation as follows:

$$f(x_i) = \sum_{j=1}^{k} b_j(x)\beta_j \tag{3}$$

Where k is the basis dimension, which controls the degree of model smoothness.

One possibility for choosing the degree of model smoothness is to use backward selection to select k. However, such an approach is problematic. A model based on k-1 evenly spaced knots will not generally be nested within a model based on k evenly spaced knots. It is possible to start with a fine grid of k knots and simply drop knots sequentially, as part of the backward selection, but the resulting uneven knots spacing can itself lead to poor model performance. Furthermore, the fit of such regression models tends to depend quite strongly on the locations chosen for knots.

An alternative is to keep the basis dimension fixed at a size a little larger than it is believed could reasonably be necessary, but to control the model's smoothness by adding a "wiggliness" penalty to the least-squares fitting objective. Therefore, rather than fitting the model by minimizing

$$\|y - X\beta\|^2 \tag{4}$$

it could be fitted by minimizing

$$\|y - X\beta\|^2 + \lambda \sum_{j=2}^{k-1} \left\{ f(x_{j-1}^*) - 2f(x_j^*) + f(x_{j+1}^*) \right\}^2 \tag{5}$$

Where the summation term measures wiggliness as a sum of squared second differences of the function at the knots (where * notes that even knot spacing has been assumed). The smoothing parameter, λ, controls the trade-off between the smoothness of the estimated f and fidelity to the data. $\lambda \to \infty$ leads to a straight line estimation for f, while $\lambda = 0$ results in an un-penalized piecewise linear regression estimate.

According to Wood (2017), representing the smooth model terms using a spline basis is likely to obtain substantially reduced function approximation errors for a given dimension of a smoothing basis. There are various types of splines in use, and the most common ones are Cubic Regression Splines, P splines, Thin Plate Regression Splines (TPRS). For a given basis dimension, TPRS outperforms both the cubic regression spline and the P spline. Therefore, TPRS is selected as the splines for constructing GAMs in this paper, though it is slower to set up than the others.

As mentioned before, the distribution of the dependent variable values needs to be determined before constructing a GAM. Considering that the values of the datasets in this thesis are almost all continuous and positive and after several set-up tests were performed, Gamma distribution was chosen combined with a logarithmic link function.

There are various methods and tests for evaluating the regression results, and generally applying only one of them is not enough to judge the model performance. Therefore in this case adjusted R-square in combination with Generalized Cross Validation (GCV) is used.

In statistics, the adjusted R-square, also known as the coefficient of determination, is the proportion of the variance in the dependent variable that is predicted from the independent variable(s). R^2 normally ranges from 0 to 1, and the bigger, the better. The most general definition of R^2 is as follows:

$$SS_{tot} = \sum_i (y_i - \bar{y})^2, SS_{reg} = \sum_i (f_i - \bar{y})^2, SS_{res} = \sum_i (y_i - f_i)^2, R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{6}$$

Where y_i are the observed values of the dependent variable, f_i are the predicted values fitted by regression, $\bar{y}$ is the mean of the observed data, SS_{tot} is the total sum of squares (proportional to the variance of the data), SS_{reg} is the regression sum of squares and SS_{res} is the residual sum of squares.

As mentioned before, the smoothness of models are usually controlled by the smoothing parameter, λ, and if λ is too high then the data will be over-smoothed while if it is too low then the data will be under-smoothed: in both cases, this will mean that the estimated smooth function will not be close to the true one. Therefore, when evaluating a GAM, the choice of the smoothing parameter requires attention, which could be measured by the Generalized Cross Validation (GCV) score. The selection of the option with the lowest value for GCV is recommended. The calculations were performed in R, using the mgcv package (Wood, 2017), it is the most common and mature implementation of the theories. It also automatically uses the lowest GCV score to select the right smoothness.

4. Variable Identification

Based on the maritime specific and more general literature three main categories of variables are identified to influence newbuilding prices; Cost related variables, Asset pricing related variables, and Supply-demand related variables. Within the cost-related variables ship construction costs, such as materials and wages are mentioned (Beenstock, 1985, Hawdon, 1978, Stopford, 2009, Tsolakis, 2005) to have a positive relation with the price, while government subsidies (Stopford, 2009, Tsolakis et al., 2003) and exchange rates (Pruyn, 2013, Stopford, 2009) have a negative relation with price. The final variables identified in this group, inflation (Stopford, 2009), LIBOR (Pruyn, 2013, Stopford, 2009) and Shipyard size (Adland and Jia, 2015), all have a positive influence on price.

For the asset pricing related variable, only lead time (Adland et al., 2017, Bertram, 2003) has a negative relation, while market indicators, like freight rates or the Baltic Dry Index (BDI) (Hawdon, 1978, Stopford, 2009, Tsolakis et al., 2003, Volk, 1994) and substitutes in the form of secondhand vessels (Adland et al., 2006, Beenstock, 1985, Beenstock and Vergottis, 1989, Haralambides et al., 2005, Strandenes, 1986) all are expected to have a positive relation with the price.

Finally, the supply-demand side is represented by two variables, shipyard capacity (Jin, 1993, Stopford, 2009) and the order book (Jin, 1993, Tsolakis, 2005). Although the first is identified as a positive relationship, the order book shows ambiguous behaviour. This can be explained by the fact that the order book might increase due to low prices (bargain shopping) but also due to high demand and consequently high prices (fear of missing out). Hence, its performance will be interesting to evaluate.

As mentioned in the literature study, vessel properties have so far not been investigated as part of the price determination. However, geared ships (equipped with own cranes), have an advantage over other ships in underdeveloped port trades, whereas ice class is required to trade in the Baltic in the ice season, higher deck strengths, more holds and a lower or larger volume to DWT ratio all influence the trades and sub-markets a ship can successfully supply. This means that technical features have both a cost aspect as well as a market aspect in them. They cost money to install but open up a particular sub-market not accessible without them. The following design parameters are considered for the newbuilding price considering this dual role: DWT, grain capacity, horsepower, speed, # of holds, gear, ice-class, strengthening.

For shipbuilding, only two authors (Jin, 1993, Volk, 1994) discuss factors influencing lead time. Considering that shipbuilding is in general an Engineering to Order (ETO) industry the literature search was extended to include other ETO lead time studies. This investigation showed that lead-time estimation is not straight forward (Kawasaki et al., 2015, Mourtzis et al., 2014, Nyhuis et al., 2005, Okubo et al., 2000, Öztürk et al., 2006, Parlar, 1997, Pfeiffer et al., 2016, Seyedhosseini and Ebrahimi-Taleghani, 2015). In many cases besides statistics also simulation, queuing theory, logistic curves, stochastic analysis, and even artificial intelligence is used to estimate lead times. Generally, it is believed that lead-time is mainly affected by the producer's capacity, scheduling, batching, and product complexity, etc. Currently, Artificial intelligence is receiving the most attention, however often regression is used as the primary technique for identifying relations and influences. It was, therefore, decided to also apply GAM on the lead time and to deduce as much as possible the relevant variables, as there were no extensive literature sources available. Given the available data and information, the variables of lead times for bulk carriers are categorized into three groups: shipyard related, vessel related and market related.

The lead time consists of the time waiting until it makes sense to start production and the construction time. The construction time of the vessel is largely determined by the shipyard characteristics. How is the vessel build, how much is subcontracted, what are regular working hours, all influence the construction time. As the lead time cannot be less than the construction time, this is the first set of variables to identify. Commonly available data on shipyards capacity is mainly in terms of total area, erection area and capacity for moving blocks (Pires Jr et al., 2009), affecting overall productivity and building time. Furthermore, moving capacity is critical in the short term, but it is not a long term or permanent bottleneck (Pires Jr et al., 2009).

When it comes to manufacturing industries, facilities can never be neglected. For shipbuilding, docks and berths for construction are the most representative ones, and the number of them can somehow reflect a shipyard's building capacity. Shipbuilding is a labour-intensive industry, so the workforce conditions should be considered too. Usually, a factory's workforce is evaluated from different aspects, such as worker education level, worker average age, availability of qualified workers, etc. In this case, the total workforce, including permanent employees and contracted employees, is taken into account; as such detailed information is not readily available. Intuitively, the maximum annual DWT output of all the vessels during a certain period can represent a shipyard's capacity over that time. However, due to economic circumstances, this may vary significantly from year to year. Therefore, capacity utilisation expressed as the output of the current year divided by the maximum output in the investigated period (Eq. 7) is also introduced.

$$Utilization\_Rate = \frac{Output_x}{\max(Output_i)} \tag{7}$$

In certain research technological advancement is used as a variable too, however, this is always established using expert opinions and lacks a clear quantified definition. Therefore, technological advancement will not be used in this model. Another aspect that is important, but cannot be obtained effectively is the lead time of so-called long-lead items, such as engines (Pires Jr et al., 2009) and other specialized equipment. In some cases, the timing of the delivery of the engine is causing a delay in the entire project. In busy times this can be important but unfortunately has to be neglected for now. Finally, many aspects of productivity are related to the country the yard is located in as well, this may represent wage levels, productivity levels, education level as well as common working times, holiday periods and other cultural factors that could influence productivity and therewith the construction time.

For the ship attributes, CGT could be considered, but as stated before, detailed aspects of the complexity might be missing in this approach; hence it was chosen to include the same technical aspects of gear, ice-class strengthening, speed, power installed, DWT and grain capacity. Finally, a higher price might be paid for a shorter lead-time, to check for this newbuilding price is included as a variable as well. For the market related variables, also a similar set as for the price under asset pricing and supply-demand is considered; time charter rates, BDI, order book, and LIBOR.

5. Data collection and validation

Data from Clarkson (2019) has been used primarily, though as several identified elements were missing, also shipyard websites were consulted. Bulk carriers were selected as a sub-set to investigate, without any clear preference, except that it is a large data set. For the newbuilding price, a lot of data points are missing before January 2000, hence the period investigated is the newbuilding price of orders between 01/01/2000 and 31/12/2017. Later is not possible because the vessel also needs to be delivered already in order to know the lead time. Within this period 1780 vessels were ordered and have a price registered in the database. For the lead-time investigation, the individual yard aspects play a key role, hence the focus has been on the top 50 dry-bulk shipbuilders resulting in a slight shift of the period to 01/01/2006 to 31/12/ 2017, as the data between 01/01/2000 and 01/01/2006 is incomplete for a large number of these shipyards. In this period 3986 bulk carriers were constructed by this group. Both periods contain an economic boom and bust to make sure the model is valid for an entire cycle. After studying the data several limitations were observed:

1. Size Group Classification: Generally, according to the size, bulk carriers are categorized into several groups Handysize, Handymax, Supramax, Panamax and Capesize. However, the classification method varies and even overlaps between different data sources. In this paper the following categories are used: Handysize (10,000-39,999 DWT), Handymax (40,000-64,999 DWT), Panamax (65,000-99,999 DWT) and Capesize (100,000+ DWT).

2. Interval: Time series are often available with various intervals (e.g. daily, weekly, monthly and yearly). Considering negotiations will take several weeks, if not months, it was decided to strive for monthly data as a fair representation of the situation at the signing of the contract.
3. Missing records: Not all variables are recorded consistently in the database. In the case of ice-class, it was assumed that no record would also mean no ice class, however for hull type or engine type, it is not valid to assume this and the data option may need to be discarded if registration is very low.
4. Labour Costs: Labour cost data was not available for China, therefore all labour costs have been replaced by the GDP per capita as a proxy for wage cost levels as recommended by the International Labour Organization (Koehn, 2008). This data is only provided annually, but wages are not as volatile as freight rates, hence this is not considered a major issue.
5. Government subsidies: This variable is often intentionally obscured or not recorded at all. It has been left out of the model altogether, but with reliable (historic) data, this would be interesting to add in the future.
6. Exchange rates: due to the large variations in absolute values for different countries these have been indexed against the 2000 value for each country (Pruyn, 2013).
7. Inflation: US inflation is considered as shipbuilding is primarily a dollar trade.
8. LIBOR: the 3-month USD based LIBOR is used for the same reason US inflation was selected.
9. Time Charter: In this case, the 1-year time charter series for each size class was selected, as a relevant representation of the market.
10. Secondhand prices: Both the combined secondhand price index and the price series for each relevant size class are considered.
11. Shipyard capacity; due to the relatively low number of prices available (~15%), more data is required for this model. A negative effect of this is that not for all yards there is sufficient data available to determine capacity utilization. As a result percentage of the fleet on order had to be used as a proxy for the NB price model.
12. Shipyard classification: The classification of Clarkson (2019) is applied: very small (<0.049 million CGT), small (0.049~0.1 million CGT), medium (0.1~0.49 million CGT), large (0.49~1 million CGT) and mega (>1 million CGT).
13. Yard Area: due to many inconsistencies in the data of the production area, the total yard area had to be selected.
14. Gantry cranes: due to insufficient and incorrect data, this variable is removed from the set.

15. Docks: This number is based on shipyard company websites rather than a central database and may be less accurate. It represents any major building or launching location, including slopes and lifts.
16. Number of Employees: no reliable and consistent data is available, hence this variable had to be removed
17. Speed: Missing in several cases but completed from other sources such as AIS websites (Traffic, 2019, Vesselfinder, 2019) and compared with peers for validity
18. Newbuilding price: for the lead time model only about 1/6th of the contracts mentions a price, hence this variable should not be relied on too heavily.

Table 1 – Data availability for both models

	Variable (NB-Price)	n	Variable (Lead-time)	n
1	Price	1625	Lead-time	3801
2	Price/DWT	1625	Total area	3517
3	DWT	1625	# of building locations	3801
4	Grain Capacity	1594	Max DWT output	3801
5	Horsepower	1625	Utilisation rate	3801
6	Speed	1625	DWT	3801
7	No. Holds	1622	Horsepower	3801
8	Lead time	1625	Speed	3801
9	Time charter	1625	Price (NB)	645
10	BDI	1625	Time charter	3801
11	SH Price	1625	Orderbook %/total fleet	3801
12	SH Price index	1625	Orderbook %/Group	3801
13	Exchange Rate	1625	LIBOR	3801
14	Inflation	1625	Builder Country (category)	3801
15	LIBOR	1625	Ice Class (binary)	3801
16	GDP per Capita	1625	Strengthening (binary)	3801
17	GDP per Capita Growth y/y	1625	Geared (binary)	3801
18	Steel Price	1625	Shipyard size (category)	3801
19	Orderbook %/total fleet	1625		
20	Orderbook %/Group	1625		
21	Builder Country (category)	1625		
22	Ice Class (binary)	1625		
23	Strengthening (binary)	1625		
24	Geared (binary)	1625		
25	Shipyard size (category)	1625		

Source: (Clarkson, 2019)

After checking the relationships between the main variable (price or lead-time) and the explanatory variables as well as removing any unexplainable outliers, the following data sets were available to estimate the GAMs with (table 1). The bottom of these lists consists of discrete variables either in the form of binary variables (indicated as ‘binary‘) and variables with multiple categories (indicated as ‘category‘). Furthermore, it may seem that there are many more variables for the newbuilding price (NB); however, this overview includes several options for a considered aspect, in total there are 21 variables for NB and 17 for lead time.

The first step in the model creation is to check for multicollinearity amongst the collected variables. For the newbuilding price multicollinearity is present in two groups of variables. The first group consists of DWT, grain capacity, horsepower and # of holds. All these variables can be related to the size of the vessel. On checking the pairwise estimation of the variables, the multicollinearity seems not applicable for the combination of DWT and # of holds but does hold for the other 3 variables in combination. As DWT is the most common representation of size and trade capacity, this variable is kept, while grain capacity and horsepower are discarded, # of holds is also maintained.

The second group consists of time charter, BDI, SH price, SH price index, order book, and steel price. Inflation and LIBOR are also showing collinearity with BDI, but not with the other variables. On inspection of pairwise estimations, the multicollinearity for order book and steel price is not affecting the estimation. The remaining four price variables (BDI, SH Price, SH price index and time charter) will be tested individually to select the best option, but will not appear in a model together.

For the lead time model, there were some indications of multicollinearity based on high correlation coefficients; however, an inspection of the pairwise models identified no significant issues at this stage. As with the NB variables, these variables will remain to be monitored during the backward elimination process.

6. Model selection & Results

Although size group specific models were created in both the newbuilding price and lead time models, the use of the full data set led to a better fit. The fact that size groups based only on DWT may contribute to this and could be explored further in the future. The backward elimination of variables for the NB Price resulted in the elimination of strengthening, yard size and geared based on lack of significance. When comparing the model fit (R^2 and GCV) the model with SH-price outperformed the models with BDI, SH price index and time charter rates. The difference between the order book as a percentage of the total or as a percentage of the specific size group was ambiguous.

The second step was to investigate the smooth terms as significant deviations from the single variable estimations would indicate collinearity. Both order book as a percentage of the total and steel price were eliminated due to this. Although not significant enough to suggest elimination, the variables speed, # of holds, lead time, GDP per capita, exchange rate, inflation, and LIBOR all showed small anomalies in their smooth terms, mostly in sparsely populated areas. To counter this and avert the risk of overfitting the model, these terms were converted to linear terms.

As a result of this speed, lead time and inflation became insignificant and were eliminated from the model. The final NB price model therewith becomes:

$$\begin{aligned} g(E(NB_i)) &= \beta_0 + s(DWT_i) + s(Orderbook\%total_i) + s(SH\_price_i) + \beta_1 \#ofHolds_i \\ &+ \beta_2 GDPperCapita_i + \beta_3 Exchangerate_i + \beta_4 LIBOR_i \end{aligned} \tag{8}$$

Table 2 – Statistical Results of NB Price estimation

Parametric Terms	**Estimate**	**P-Value**	**Significance**
Intercept	3.513	<2E-16	***
# of Holds	0.05630	<2E-16	***
GDP per Capita	4.860E-6	<2E-16	***
Exchange Rate	-0.3640	2.23E-15	***
LIBOR	0.02840	<2E-16	***
Smooth Terms	**EDF**	**P-Value**	**Significance**
s(DWT)	8.919	<2E-16	***
s(Orderbook%Group)	8.081	<2E-16	***
s(SH price)	8.739	<2E-16	***
Model Fit			
R^2 (adj.)	0.9341		
GCV	0.01527		
N	1622		

Signifi. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Source: Author

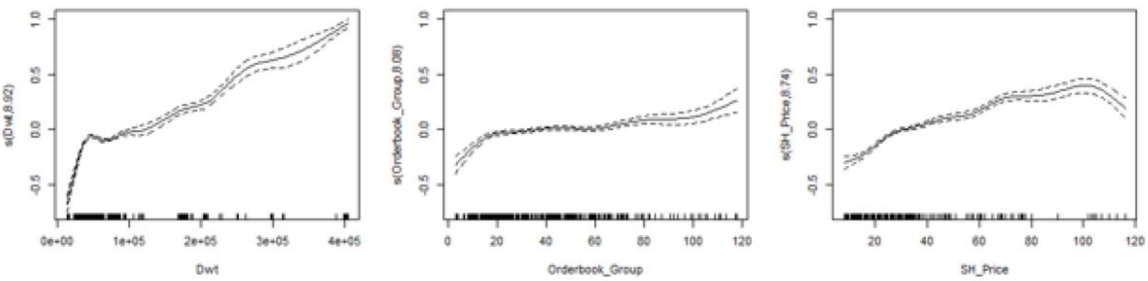

Figure 1 – Smooth terms in the NB price model

Source: Author

In Figure 1 the smooth terms are presented and in Table 2 the statistical output of the estimation. The fit is very good ($R^2 > 0.9$). The left plot (Figure 1) shows the relationship between DWT and Price that the sale prices of new bulk carriers are positively related to DWT, especially true for Handysize and Handymax, where the prices rise dramatically with the increase of DWT. The middle plot indicates the positive influence of demand for new bulk carriers on newbuilding prices. When the order book size is at low levels, newbuilding prices are sensitive to a rise or fall in the order book. After the order book size becomes larger, the effect is still positive but more ambiguous, as can be expected given that this situation is not seen that often, basically only around the last boom and crisis. The rightmost plot suggests how secondhand prices affect newbuilding prices. The sale prices of vessels generally increase as secondhand prices grow, except at the end of the curve there is a decline of newbuilding prices. This exception might result from the low density of data within that range, or prices were so high, that newbuilding became too risky at similar prices, due to the delay in delivery.

For the lead-time, a choice needs to be made between order book as a percentage of the total fleet and order book as a percentage of the size group. Backward elimination was performed for both options, the order book as a percentage of the total fleet outperformed the alternative and is, therefore, the only one discussed in this paper. This does make sense; yards generally construct more than one vessel type, meaning that the total order book will be more in line with their current workload than the order book of a single ship type.

Based on the lack of significance, strengthening is eliminated, similar to the NB price. However in combination with the order book as a percentage of the fleet, also the TC rate is insignificant and eliminated from the model. In the next step, the smooth terms are investigated. Horsepower and total area show strong signs of correlation with DWT and # of building locations respectively. Furthermore, speed, # of building locations and utilization rate all show some form of anomalies in areas where data points are sparse and are therefore introduced as a parametric term. In parametric form, however, both speed and # of building locations were insignificant and therefore removed from the final model. The final lead time model therewith becomes:

$$\begin{aligned} g(E(LeadTime_i)) &= \beta_0 + s(Orderbook\%Total_i) + s(LIBOR_i) + s(DWT) \\ &+ s(MaxOutput_i) + \beta_1 UtilizationRate_i + \beta_2 IceClass_i + \beta_3 BuilderCountry_i \end{aligned} \tag{9}$$

In Figure 2 the smooth terms are presented and in Table 3 the statistical output of the estimation. In this case the fit is very bad ($R^2 < 0.4$). Still the results will be discussed for completeness. It should also be noted that for the categorical variables, ice-class increases the delivery time. This seems logical as the construction of the hull becomes more complex due to the ice class. Besides, it is indicated that using China as a reference, being built in South Korea can shorten lead times while in Japan and the Philippines it takes more time to deliver a bulk carrier, which means the shipyards in South Korea would be superior to other yards in terms of lead times.

Capacity Utilization Rate is positively related to lead times, indicating that busier shipyards have to take more time to deliver a new vessel. Once more this is in line with the expectations.

When it comes to the smooth terms, Figure 2 presents the effects of the smooth terms separately. It can be seen that lead times increase as the increase of order book size when the size of the order book is below 20%, after which the fluctuations of lead times become relatively steady. An order book above 20% is rather exceptional when considering history, but very relevant in the period 2006-2009. The relationship between lead times and DWT encounters a similar changing trend. Also, there is a gap around DWT of 150,000 tons which results in a very broad confidence interval. Besides, Max DWT Output is generally positively related to lead times though it may not be reliable due to the low density of data points. Similarly, LIBOR also presents an overall positive influence on lead times.

Although this all seems promising, the usefulness of the model is unsatisfying with an R^2 of only 0.3632. To identify a possible root cause for this low value four actions were executed: the model validity is checked, the main discontinuities are eliminated, the model is applied to a single shipyard, and variable choices are reviewed.

Table 3 – Statistical Results of Lead time estimation

Parametric Terms	**Estimate**	**P-Value**	**Significance**
Intercept	4.855	<2E-16	***
Utilization Rate	0.1729	1.27E-11	***
Ice Class	0.00135	5.36E-8	***
Builder Country(Japan)	0.04621	2.21E-3	**
Builder Country(South Korea)	-0.3485	<2E-16	***
Builder Country(Philippines)	0.2386	1.99E-13	***
Smooth Terms	**EDF**	**P-Value**	**Significance**
s(Orderbook%Total)	8.114	<2E-16	***
s(LIBOR)	8.730	<2E-16	***
s(DWT)	8.778	<2E-16	***
s(MaxOutput)	8.832	3.34E-14	***
Model Fit			
R^2 (adj.)	0.3632		
GCV	0.1115		
N	3801		

Signifi. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Source: Author

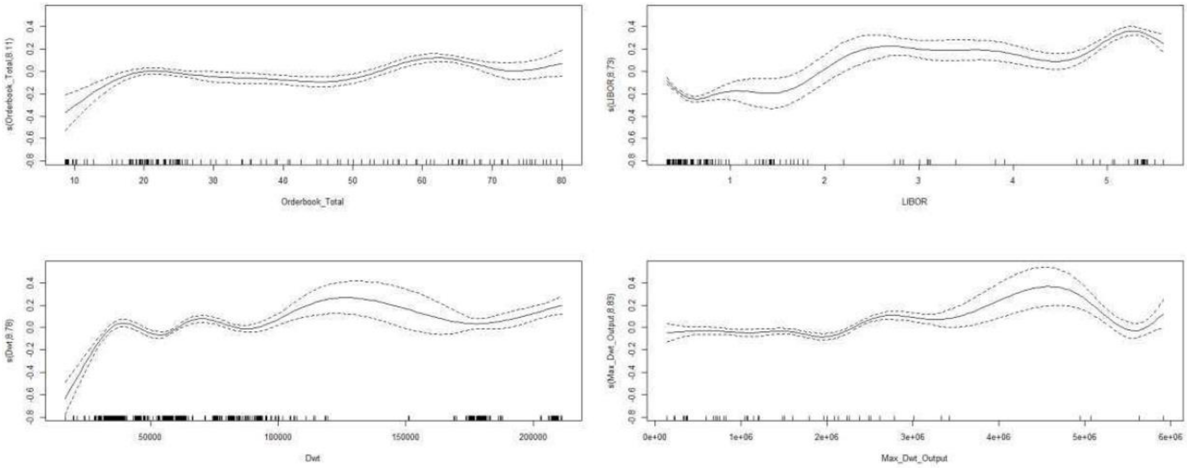

Figure 2 – Smooth terms in the lead time model

Source: Author

The first check is to see if the assumptions underlying a GAM are not breached. This is done through the four graphs in Figure 3. The upper left QQ (quantile-quantile) plot is very close to a straight line, suggesting that the distributional assumption is reasonable. The upper right panel shows that the variance is approximately constant as the mean increases, suggesting that the constant variance assumption is tenable. The histogram of residuals at the lower-left seems approximately consistent with a normal distribution. The lower right plot, of response against fitted values, shows a positive linear relationship with a good deal of scatters, except some outliers. So the conclusion is the data does not violate the model assumptions.

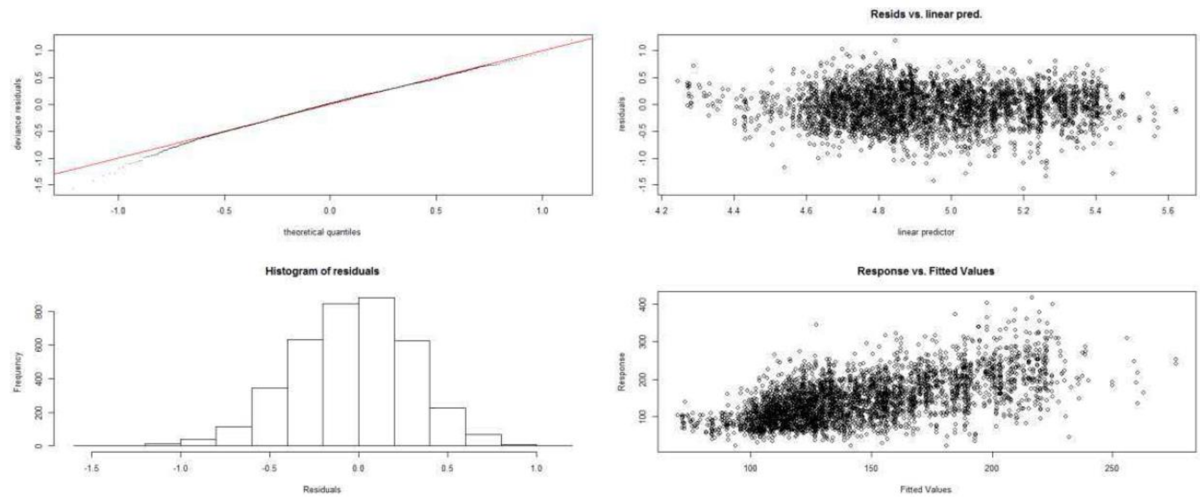

Figure 3 – Model Validity Plots

Source: Author

Secondly, the bad fitting result is due to the discontinuity of some variables of the dataset. It can be seen that for “DWT” there are no values around 150,000 tons and only a few shipyards have a “Max DWT Output” of more than 4,000,000 DWT. To verify this point, the dataset is processed again by deleting all the fixtures with a “DWT” of more than 100,000 tons or a “Max DWT Output” of more than 3,500,000 DWT. With the same modelling method from start to end, a new model using the modified dataset is established. Builder country is removed in this final model, all other variables are present in the same form as the original model, however, the R^2 has deteriorated to 0.3460. This leads to the conclusion that the discontinuity is not the main cause of a bad fit.

Thirdly, the current model contains many shipyards, which means that lead time is influenced by difference in production depth (to what extent is production done in-house or outsourced), production philosophy (How is production managed or optimised), series sizes and many other variables which cannot be collected without detailed yard observations or interviews. To check the effect of these aspects, one yard with good data availability was selected (Oshima Shipbuilding) and the model was recreated with the same procedures. Both builder country and max output were eliminated in this process. This makes sense as they are constants in this model. However, the final model does see R^2 increase to 0.4394 for this particular shipyard. This is a significant improvement, however nowhere near the levels of the NB price model.

Finally, the variables selected are reconsidered. From a building perspective, CGT might be more relevant than DWT (Adland et al., 2017), this was checked, but did not result in a better fit either. The absence of some crucial variables is also considered For instance, according to Pires Jr et al. (2009), the shipyard building capacity is mainly expressed in terms of the erection area. Also, as already mentioned in the variable discussion the lead time of important equipment may be of influence. Unfortunately, this data was not available to us at this stage but might improve the lead time model in the future.

7. Conclusions

As a general conclusion, it can be stated that, given necessary data and information, GAM is capable of estimating the linear and nonlinear relationships between the dependent variable and various independent variables. Thus, when having access to the data related to the shipping and shipbuilding market, using GAM to estimate bulk carrier’s newbuilding prices and lead times is reasonable and practical.

Furthermore, it could be concluded that the newbuilding prices of bulk carriers can be be estimated with a high fit ($R^2 > 0.9$). The newbuilding prices are mainly affected by vessel size (DWT), shipping market status (secondhand prices) and the demand for new vessels (order book size as the percentage of corresponding size group fleet), all of which have a strong positive influences on the prices, with the vessel size as the most influential one. This also suggests that newbuilding prices are cost-driven, which conforms to the economic theory. Besides, the positive effects of number of hatches, GDP per capita and LIBOR, together with the negative effect of exchange rates, are also in line with the theoretical expectations. Besides, it is demonstrated that the scale of the economy is also applicable to the newbuilding market since the price per DWT decreases with vessel sizes.

Another conclusion, is that the fit for lead-time is not very good. With an R^2 below 0.5 in the best case, the model fit is not very high. To find the causes, four tests were executed. Based on these, it appears that the differences in approaches to shipbuilding of individual yards and potentially the lack of one or more detailed variables are the causes of the bad fit for the lead time model. In general, the lead time of bulk carriers appear to be mainly positively influenced by vessel size (DWT) and the demand for new vessels (order book size as the percentage of total bulk carrier fleet). Similarly, the maximum DWT output and capacity utilization rate of shipyards, LIBOR and having Ice Class also indicate positive influences. Moreover, concerning lead-times, China and South Korea show superiority to Japan and the Philippines. However it is advisable to apply this model on a specific yard or only to predict lead time increase or decrease on average when applying it worldwide, due to the indicated low fit.

The current approach used the full size range and economic cycle. A sub-division based on DWT was also tested in this research, but performed worse than the full size range. The fact that DWT is a rather crude way of grouping ships is seen as one of the reasons for this. Using a more sophisticated grouping of ships, e.g. based on main dimensions and trade, might outperform the current models. Another aspect to consider is that people act differently in a boom and a bust. Splitting the economic timing could also be interesting to identify such differences.

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