

Ship Valuation

For CMS, LLC

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Executive Summary

This report showcases the detail analysis made by our company *Compass Maritime Service LLC*, to estimate the price of the ship *Bet Performer*, in order to persuade our client into making the right decision and buy this particular ship. Our report predicts the estimated price value based on the comparison of various ships closer to the *Bet Performer*; using Year built, Dead-Weight Tons, Age at sale and Capsize information as reference. We support our data and statistical reasonings mainly with the help of Multiple linear regression, and as a secondary option, KNN regression model.

Situation Analysis

We have in our hands a potential client interested in purchasing a ship, a capesize bulk carrier to be specific. Therefore, we referred this case to our head of the firm's valuation practice, Mr. Basil Karatzas. Mr. Karatzas main objective is to find an appropriate ship, according to the client's needs, and propose a reasonable and competent price which would help the client finalize the deal. Throughout the basic process, the *Bet Performer* was found to be the best option for this potential client. An 11-year-old,

Hypothesis

On eyeballing the ship data, we found that some variables had a greater impact on its

Some initial findings:

1. In general, there was a downward trend of average price as we increased the age, but there were few pockets (Ships aged 18-19, 14-

About Us: At *Compass Maritime Service LLC*, we specialize in sale and purchase of ships and offshore vessels, valuations, recycling and demolition of ships, shipping research, and consulting. We are proudly considered as one of the leading ship sale and purchase brokerage companies in the United States with broad international recognition.¹

*"We have a large international network within the shipping and offshore industries that enable us to use our extensive experience to provide an excellent number of businesses opportunities for our clients."*¹

172,000 DWT capsize bulk carrier. However, when it comes to valuating a ship there are some risks to be considered. For instance, the volatility of the market and competitors. In order to value the *Bet Performer* and close the deal, our estimated price must stay competitive. Not too low so buyers can take us seriously, and not too high, so our buyers won't lose interest.

price while some could be ignored for calculating the ship price.

15) (*Exhibit A*) that were off. On an average, ships having a sale price equal to or more than 100 million are aged less than 10 years with a few exceptions.

2. Analyzed the relationship between deadweight ton with the price. We assumed that more DWT (i.e. more capacity valued if they weigh in the range of 170-175 DWT (*Exhibit B*). This might be because of better fuel efficiency of this deadweight class or because of some other variables affecting the price.

3. Baltic-dry capesize index values increased by approximately by 169% in the given time frame. Although we knew that this cannot be the sole criteria determining the ship price, it had to be one of the key factors. We considered two sets of ships to verify the relation of capesize index with ship price keeping other variables like age and DWT almost similar (*Exhibit c & d*). Analysis indicated that similar ships were sold for more if the capesize index value was more.

Age	Average of Price(in millions)
3	100.00
4	156.50
5	133.00
6	111.75
8	78.00
9	135.00
10	50.50
11	81.55
12	68.40
13	64.38
14	79.15
15	87.35
16	45.00
17	57.23
18	82.00
19	83.00
20	56.33
21	41.00
22	31.00
23	40.00
24	38.00
26	23.50
Average price	72.96

Exhibit A

DWT ranges	Average Price (in millions)
95-100	35.00
120-125	43.00
135-140	38.00
140-145	22.00
145-150	64.05
150-155	55.10
155-160	61.50
160-165	73.30
165-170	68.75
170-175	102.57
180-185	83.70
185-190	78.00
205-210	83.00

Exhibit B

Vessel	Price(in millions)	YearBuilt	Age at Sale	DWT	Capesize	SaleDate
Martha Verity	60	1995	12	158	4647	1/1/2007
Spring Brave	62	1995	12	151.1	4647	1/1/2007
Martha Verity	63	1995	12	158	5245	3/1/2007
Formosabulk Allstart	67	1995	12	150.4	5752	4/1/2007
Tiger Lily	90	1995	12	149.2	8886	10/1/2007

Exhibit C

Vessel	Price(in millions)	YearBuilt	Age at Sale	DWT	Capesize	SaleDate
Orient Fortune	28	1984	23	161.4	6618	6/1/2007
Great Moon	30	1984	23	146	6980	7/1/2007
Marine Hunter	45	1984	23	164.5	8886	10/1/2007
Peace Glory	57	1984	23	166.1	8886	10/1/2007

Exhibit D

Statistical Reasoning

In our previous report, we found the correlations of all the independent variables with respect to price, shown in *Exhibit E*. However, the correlations only gave the direction of relationship and not the magnitude. In order to get the

magnitude of their influence, we ran single variable regressions for three variables that are most logically related to price: Age, Deadweight tons, and Capesize index. *Exhibits F, G and H* show the linear regression results of price

w.r.t age at sale, Dead-weight ton (weight) and capesize index respectively.

Price	YearBuilt	Age at Sale	DWT	Capesize	SaleDate
1	0.81	-0.79	0.51	0.35	0.35

Exhibit E

Goodness of Fit: Furthermore, we used the AIC test (**Exhibit I**) in R, to find out what factors would predict the price of the ship best. AIC is a number that is helpful for comparing models as it includes measures of both how well the model fits the data. A good model is the one that has minimum AIC among all the other models.

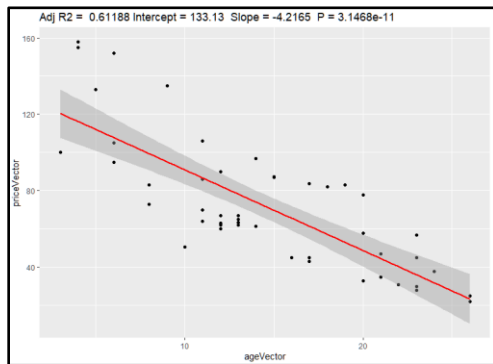


Exhibit F

In conclusion, using variables - Age at Sale, DWT and Capesize will give better results than using all the variables given in the dataset.

One Variable Model

For this model, we performed regression of price with respect to the age at sale (which is most correlated to price compared to the other two variables (**Exhibit F**)). As we are only considering a single predictor in our model, the accuracy of the model is low. Further in our research, we used R squared metric to measure how well our model is fitting the data. As we can never actually get the exact true value of the ship, we can

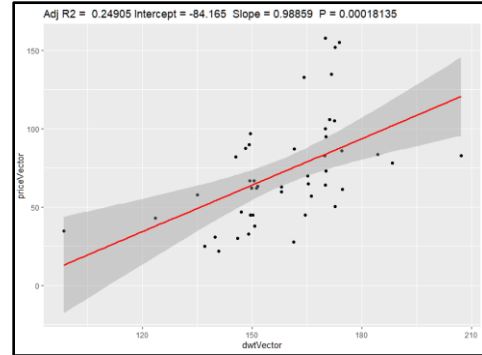


Exhibit G

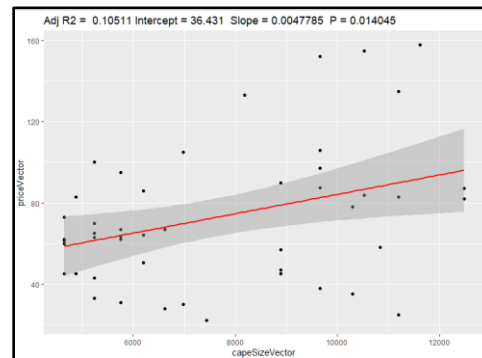


Exhibit H

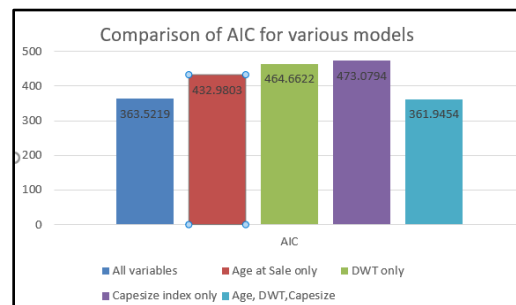


Exhibit I

look at confidence interval to account for the uncertainty (Results below).

Single Variable Model	Bet Performer
Estimated Price	87.65M
R Square	62%
95% confidence interval price	79.83M - 93.67M
95% prediction interval	43.68M - 129.81M

Multivariable Model

To tackle the low accuracy faced in single model we designed a Multi-Linear regression model with three main predictors (Age, DWT and capesize of the ship).

	Estimate	Std.Error	t value	Pr(> t)
(Intercept)	44.2255	16.3832	2.699	0.00982
ageVector	-4.5438	0.2614	-17.378	< 2e-16
dwtVector	0.2421	0.0916	2.643	0.01134
capeSizeVector	0.0072	0.0005	12.051	1.57E-15

Multi Variable Model	Bet Performer
Estimated Price	125.83M
R Square	92%
95% confidence interval price	118.89M - 132.77M
95% prediction interval	104.74M -146.92M

Exhibit J

After running the regression of Sale Price on these 3 dependent values, we found the summary of the model which is highlighted in **Exhibit J**. From this model we can safely assume that the variables we considered, had the p-value within the acceptable range. Using R squared we could explain about 92% the changes in price of a ship based on these 3 variables variable values.

"If we increase the age of the ship by 1 year keeping other variables constant, price goes down by 4.54M. Similarly, if we increase the capacity(DWT) by 1 unit, price will go up by 0.24M and if Capesize index value increases by 1000 points, price will go up by 7.2M"

The other plot from the Regression model that better explained the fitting and the prediction was the Residual vs Fitted graph (see exhibit K). What this model helped us understand is how well did our model fit all the data points. Considering the range of prices in the x-axis, and the dotted line signifying the linear model, we see that there is a small degree of non-linearity, which is primarily because the data wasn't normalized. It also helps us understand that there are data points which are far away from

the model. These observations can be called as outliers, but as they have a relation to the model, we can call them the extreme values.

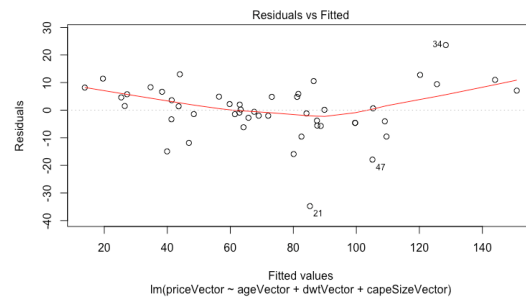


Exhibit K

The next graph that gave us an understanding of how all the examples of residuals be compared against the theoretical distance of the model. (See exhibit L).

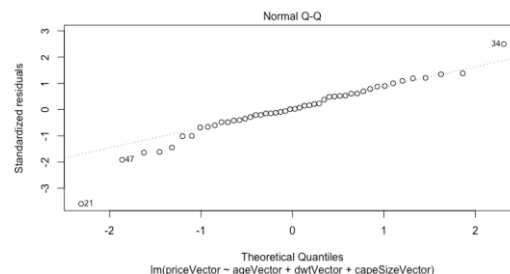


Exhibit L

While most of the observations lie around the line, which represents the model, the extremes on both ends have some outliers. To understand more on the data points and the distribution of the residuals around the model with respect to the price, we looked at the next graph(Exhibit M).

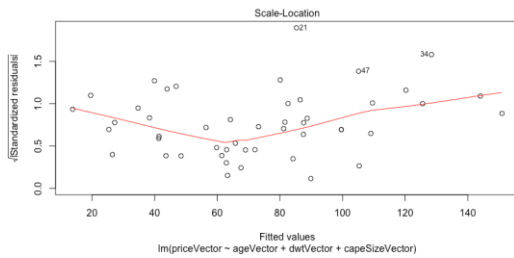


Exhibit M

This graph shows that for higher price we have less observations and the scatter of the observations around the model is greater. But for the medium price range the observations follow the line very closely. These were the interpretations from this model that we had and found to be the best fit among the three.

Prediction: We ran several experiments to check how the price of Bet Performer changes when we change the variables it depends on and the results are as follows:

Criteria	Estimated Price
5 years younger	144M
DWT less by 20K	120.99M
Capesize index 30% lower	98.85M

Limitations:

1. There might be outliers in the dataset which will cause the regression output to change drastically.

Conclusion

The goal of our team was to offer a reasonable price for the bet performer. After all the analysis, with a confidence interval of 95%, we came

Recommendation

This regression model was constructed on a relatively small sample size even if we consider large cargo ships to not sell as frequently as

2. We don't know the charter rates or how many similar ships are already present in the market. Such factors will alter the sale price.

3. The most important factor affecting ship prices ought to be the demand for the commodity they are carrying. In our case, the ship in question is a capesize one and such ships are generally used for transporting ores and minerals. The Baltic dry capesize index is an indicator of this demand. Also, as mentioned before, the market is volatile, so we can expect fluctuations in the Baltic dry index which might heavily sway the prices.

4. Moreover, capesize ships are used for transporting mineral and ores; it might be of interest to the buyer, the type of coating present on the inner walls of the container. If Bet Performer has a special coating which can help the buyer expand their product base, the ship would be highly valued. Similarly, if its keel is laid by a reputable brand fetches a higher price in the market. Specifications like the type of engine etc. might also affect the price. Our model doesn't account for these specifications.

up with an equitable price of \$125.83M. Though we had limitations, of only having 50 records and therefore a larger variance, we overcame these limitations to the best of our abilities and came up with a reasonable price.

other objects of transportation. A smaller sample size will produce a larger margin of error

and with a sample size which is lacking or fails to accurately represent the population. Other factors apart from the variables taken into consideration (economic conditions, engine type of the ship, transmission type, any special coating on the hull, overall demand of the

cargo ship, oil price etc.) might also play an important role in determining the price. Just because we can use Regression to borrow power and predict an accurate selling price does not mean it is a good time to sell a cargo ship. The seller needs to be careful of the market and understand exactly what a good action for him or her is. Only then will a method like regression be truly helpful.

Sources

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¹ “Compass Maritime Services: About Compass Maritime.” *Compass Maritime Services | About Compass Maritime*, http://www.compass-mar.com/About_Compass_Maritime.html.

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