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Scrapping Determinants in the Tanker Market

A vessel based logit model

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Abstract

Like many others, the crude oil tanker industry face the challenge of capital depreciation. Higher operational- and maintenance costs cause shipowners to scrap older vessels to ensure profitability. However, in good markets, old vessels are kept in service, while in a market downturn, even young vessels are sent to scrapping.

In our master thesis, we analyze the effect of vessel and market specific factors on the probability of scrapping a tanker. The analysis is constructed to reveal differences between the VLCC, Suezmax and Aframax segments, and compare periods with different market conditions. Using logit models on our data set from 2014 to 2018, results show that vessel age, scrap price and freight rates are factors impacting the scrapping decision. Increased age and scrap price increase the probability of scrapping, while an increase in freight rates decrease the likelihood of demolition. These findings are consistent for all three segments, but the results indicate that market volatility affect the largest vessels more.

Finally, we find that there are key differences between periods with different market conditions. When splitting the data in two; prior to and after September 2016, we find that in the first period with favourable conditions, only vessel age is significant in explaining scrapping activity. As the market declined, shipowners took age, scrap price and freight rate into account when scrapping. We also find that age has a stronger impact in the market downturn, indicating that as the market busts, older vessels are scrapped first.

Preface

This thesis is written as part of our Master of Science degree in Economics and Business Administration within our major Energy, Natural Resources and the Environment at NHH - Norwegian School of Economics.

Through earlier courses in shipping at NHH and work experience from the industry, we have gained insight in the tanker market. This inspired us to further develop our knowledge and contribute to research in this industry.

A special thanks to our supervisor Siri Pettersen Strandenes for impeccable guidance, feedback and discussion during this semester. It was Siri and her previous research that guided us onto this topic. We would also like to thank Øivind Anti Nilsen for his advice on the econometric modelling.

The thesis adds to the existing research on demolition activity within shipping, but to our knowledge little has been done in the tanker market alone. We hope this paper will be of interest for shipowners, investors, financial institutions, academics and other market participants. Additionally, we hope that it will be a basis for further research in the tanker market.

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1. Introduction

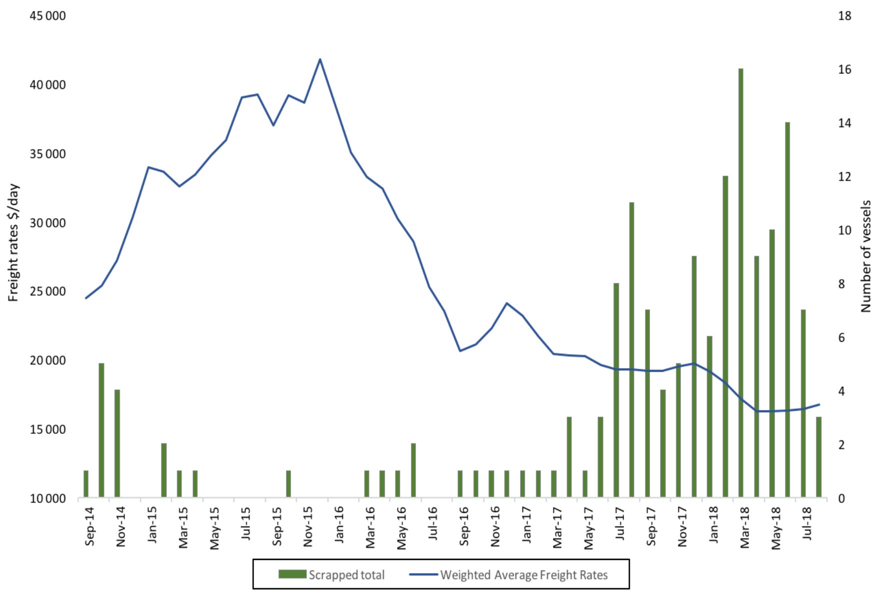
The shipping industry is cyclical by nature where freight rates and profits reach sky high levels one year and may plummet the next. Shipowners usually contract new vessels when the shipping cycle is in an upturn or at a peak to reap the benefits of high rates. However, since delivery of new ships takes 1-4 years or more, they may enter the market in a different part of the cycle. Possibly when the market is in a downturn and ships might be laid up upon delivery. During such conditions, shipowners want to reduce exposure by scrapping unprofitable vessels and increase freight rates through supply reduction. There are three ways to reduce capacity in the market; 1) speed reduction, 2) vessel lay-up and 3) vessel scrapping. Speed reduction can be done overnight as a short-term measure, lay-up is a medium-term measure since decommissioning a vessel usually takes some time, while scrapping permanently reduces capacity. The decision to scrap a functioning and relatively young ship will only be triggered by a prolonged depression with little or no prospect of recovery in coming years. Sending vessels to scrap yards is therefore considered as a last resort option for ships that can no longer operate profitably in the market. Owners could also reduce exposure by selling ships in the second-hand market. However, this could be challenging because all shipowners face the same market conditions and demand for second hand vessels is likely low. Additionally, total supply would be unchanged and this measure would therefore not increase freight rates.

Tankers differ from several other segments in the shipping industry because they transport homogeneous commodities, either crude oil or products refined from crude oil. Charterers are mostly indifferent to which tankers they hire due to similar vessels with little advanced technology. The largest differentiation between the vessels are size and operational costs, where older vessels tend to have a higher fuel consumption, inspection- and maintenance costs.

Different sized vessels operate on different routes. The largest ships, the VLCCs, are best suited for the longest intercontinental trade routes between the largest ports. Trade routes mostly operated by VLCCs are from the Middle East Gulf to Singapore, Japan and the US Gulf. Suezmaxes are mostly employed on voyages from the Black Sea to the Mediterranean, and West Africa to China, while Aframaxes are mostly used on continental routes within Europe and Asia. During a depression in the tanker market, the VLCCs are hit the hardest. Due to economies of scale these ships have an advantage during market upturns where cost per tonne of transported oil is lower. Equally, they have a disadvantage in bad markets due to the dependence of enough cargo to exploit these benefits (Stopford, 2009). The smallest segment of Aframax is in theory least affected by market volatility because the vessels operate regionally on fixed routes. Suezmax, is similar to its size somewhere in the middle, and is also the segment mostly used as shuttle tankers between offshore oil fields and onshore refineries.

The tanker shipping market have twice in the last decade entered into a prolonged depression where low freight rates have cut profits and made it difficult for shipowners to keep all of their ships employed. The first depression came during the 2008 financial crisis. Before the crisis, rates were driven by soaring demand for oil by China, India and other emerging countries. There was a deep recession until 2013, followed by three years of gradual increase in freight rates which lasted until the oil price recovery started in 2016, as shown in figure 1.1.

Figure 1.1 – Freight rate- and scrapping development from 2014 to 2018



Source: (Clarksons Shipping Intelligence Network, 2018)

Today's situation is characterized by many of the same traits as a trough. Scrapping is not high enough to compensate for the recent surplus of deliveries, freight rates are too low to operate profitably for many shipowners and second-hand prices are close to scrap prices (Stopford, 2009). As of September 2018, freight rates are as low as the direct aftermath of the 2008 financial crisis and recovery is not necessarily imminent.

While 2016 saw the lowest level of scrapping measured in deadweight tonnage since 1989, 2017 saw improvement with scrapping levels quadrupled. So far 2018 have improved further, reaching 2017 scrapping levels already in April, headed for a 7-year high. Several factors may contribute to continue the increased scrapping activity. Firstly, the IMO regulations, imposing low-sulphur fuel oil on all vessels will take effect from 2020 and increase operational costs for old ships. Older tankers will either be forced to buy an expensive scrubber, or use the more expensive low sulphur fuel oil. Not only is there a large initial cost in buying a scrubber, but ships have to conduct frequent expensive surveys, costing millions of dollars. Secondly, scrap steel prices have nearly doubled from June 2017 to 2018, mainly due to the shutdown of inefficient steel mills in China and emission regulation coming into place. Thirdly, storage of oil on old tankers have been an attractive alternative to lay-up or scrapping when freight rates are low, but has seen lower demand recently. Floating storage is an important factor to consider when analyzing the tanker market as it introduces new sources of volatility. This generates revenues and gives the shipowner the ability to employ the ships when the market recovers. It affects both the oil price and freight rates, possibly disturbing the scrapping decision. With the decreased demand for floating storage these tankers might now be scrapped.

Although many factors indicate better times for the tanker market due to increased scrapping, a large delivery volume of new tankers is set for the rest of 2018. Especially new influx of VLCCs could offset the positive market effect of the increased scrapping activity. Political developments might also put a dampener on the growing optimism. US sanctions against Iran will affect trade routes from the Middle East to Europe unless the other Gulf states are able to cover the Iranian shortfall and sustain tonne-mile demand. The United States' growing independence of imported oil will also reduce the demand for transportation of crude oil the coming years.

In this research, we use logit models to explore how the scrapping activity has developed over the last four years. First, we look at how vessel specific characteristics such as size and age impact scrapping. Later, we include different market factors such as freight rates, scrap steel price, and deliveries to see how they affect the scrapping behaviour.

The remaining structure of the thesis is as follows: Section two covers the previous research on the topic of modelling shipping markets and scrapping behaviour. Section three is an overview of the data included in the study and how they are sourced, as well as the methodology and the underlying assumptions of the estimations. In section four the results of the estimated models are reported and the findings discussed, before concluding in section five.

2. Literature Review

The shipping industry is a well developed, competitive and transparent market, resulting in volatile freight rates, newbuilding- and second-hand prices, as well as lay-up- and scrapping levels. The industry is also flexible in terms of temporary and permanent capacity retirement in crises and depressions. Koopmans (1939) was one of the first to model supply and demand in shipping, studying the determinants of freight rates.

In the 1980s, the ship demolition geographic center gradually changed from the East Asian countries of Taiwan, China and South Korea towards the Indian Subcontinent with Bangladesh as the dominating ship breaking nation today (Stopford, 2009). This shift has brought several occupational and environmental concerns to the surface, dominating the research and discussion about scrapping since the late 90s, as pointed out by Kagkarakis et al. (2016). *Beaching*, the demolition method where the ship is run aground on a beach and then taken apart is an especially controversial manner of ship demolition and has caused many countries to ban companies to take part in this practice. Sinha (1998) argued in his paper that demolition of ships in poor countries is a transfer of environmental costs from developed countries to the farmers, fishermen and workers in the ship breaking countries, where environmental legislation already is lacking. This paper was later backed by Demaria (2010). Matz-Lück (2010) studied the implementation of the Hong Kong International Convention on the Safe and Environmentally Sound Recycling of Ships in 2009. He focused on whether the convention and its guidelines would be adopted by the major shipping nations and criticized the convention for its lack of a prohibition against beaching.

A different angle to the ship demolition topic is the scrapping market itself and how it is affected by the other shipping markets; the freight-, second-hand- and newbuilding market. This was argued for by Buxton (1991), who supported that shipowners scrap ships according to the freight- and recycling market conditions. Mikelis (2013) discuss the importance of the recycling industry to the global steel production market and found that scrap steel accounted for 1,5% of the world's total supply. Merikas et al. (2015) found that the primary determinants for the scrap steel price is the average export price of scrap in the U.S and Europe. While in the countries where the demolition itself takes place, the price affects the internal demand for scrap. Kagkarakis et al. (2016) explore how freight rates affect the scrap steel prices and argue that in favourable market conditions with high freight rates, along with Chinese economic growth, scrap steel prices increase because shipowners are reluctant to sell their ships. Karlis and Polemis (2016) also found a negative relationship between freight rates and scrap price. When freight rates are high, shipowners are reluctant to scrap their ships, and the opposite is true when freight rates are low. Chou et al. (2012) studied the relationship between the Crude Oil Price and Steel Price Index and found a co-integration between the prices of the two commodities. They found that while oil is only affected by its own index movements and volatility, steel is affected by its own and the movements of oil price, also affecting the scrap steel price. Their research further revealed differences in where ships of different owner nationalities and age are scrapped.

Greenwood and Hanson (2014) studied the link between investment in boom and bust cycles, using the dry bulk sector as an example. They found that firms over-extrapolate exogenous demand shocks and do not take their competitors' investment response sufficiently into account. As a result, they end up with an oversupply of vessels a few years after a boom, in a market downturn, leading to lower rates. They found it less risky to invest in new ships during busts than booms. Beenstock and Vergottis (1989) estimated an aggregate econometric model of the tanker market using data from the 1950s to 1986, simulating a demand- and bunker price shock. Their findings show that the market cushion shocks when anticipated and that the dry bulk and tanker market have spillover effects. Abouarghoub and Mariscal (2011) showed in their analysis of freight volatilities for tanker freight returns that larger shipping segments are more exposed to market shocks.

Furthermore, Cockburn and Frank (1992) explore the question of whether the scrapping decision is determined by exogenous or endogenous factors. Market conditions are exogenous and company- and vessel specific factors endogenous. They examine the effect of changes in market conditions on the price and recycling of tankers, finding that retirement of ships do depend on exogenous market conditions. Their research show that market situation impact the scrapping decision because it affects the price the tanker could get in use, but also that less energy efficient ships with steam engines, which existed in their data period, are scrapped first (Cockburn and Frank, 1992).

Although the optimal situation for shipowners is to keep ships employed in the market, capacity retirement can, according to Dixit and Pindyck (1994) be seen as an investment when rates are unprofitable. Even though the net present value (NPV) of the ship's remaining operational lifetime turns negative, scrapping has a positive effect on the market and will improve NPV for the rest of the fleet.

In a similar angle towards the dry bulk market as we have in this thesis on the tanker market, Alizadeh et al. (2016) used logit models based on ship- and market specific variables to assess the probability of a dry bulk carrier being scrapped. They found a strong relation between age and scrapping across all sub-segments, but also differences in how different market conditions affect them. Yin and Fan (2018) also analyze the scrapping decision from the shipowner's perspective using survival analysis and the Cox proportional hazards regression model, before and after the financial crisis of 2008. Their analysis show that there is little difference in the ship specific characteristics on scrapping probability but older and less efficient ships were scrapped after 2008 because of high bunker costs combined with low freight rates. Knapp et al. (2008) explored the ship demolition market in their econometric analysis of the demolition market over 29 years across several shipping segments, demolition locations and owner nationalities. They found a negative relationship between ship recycling and freight rates and a positive relationship between scrap steel prices and ship recycling. Their research also uncovered differences in where ships of different segments with specific traits are scrapped and which nationality their owners had.

3. Data and Methodology

3.1. Data Description

After summarizing the development in the tanker market and the related literature on the topic it becomes clear that both the ships characteristics and market conditions impact the scrapping decision.

The data of operational and scrapped vessels is sourced from Clarkson's World Fleet Register and Shipping Intelligence Network over the observation period from 2014 to 2018. The ship specific data contains information about age, deadweight tonnes and the date of scrapping. Market data have also been gathered from Clarkson's and contain monthly observations of oil price, freight rates for each segment, scrap steel price, bunker prices, LIBOR interest rate and new ships delivered. The three main segments of the crude tanker market are 1) Very Large Crude Carriers (VLCC) carrying 200,000 dwt and above 2) Suezmax, between 125,000 and 200,000 dwt 3) Aframax, between 80,000 and 124,999 dwt.

Scrap steel price is calculated using the average scrap steel price of Bangladesh and the Subindian Continent. These are the two largest markets for scrapping of tankers. Although they follow each other closely, there are some variations, likely due to market conditions that affect the specific countries and areas.

The oil price used in the analysis is the Brent Crude Oil Price which serves as a major benchmark for oil prices across the world. For bunker prices, the Rotterdam 380cst high sulphur fuel oil is collected. Monthly Libor is the London Interbank Offered Rate representing the alternative cost of other investments, as well as capital expenditure for shipowners.

Freight rates collected from Clarkson's are the 1 year Timecharter Rate Long Run Historical Series in $USD per day for each segment[1]. Freight rates are measured on a monthly basis, capturing the volatility in the market. The variable *Freight Rate* is scaled with 1.000$USD, along with *DWT* which is scaled with 10.000 tonnes.

[1] Spot freight rates are in the tanker market measured in Worldscale and not comparable across years.

When pooling the data, we adjust for different rates in each segment by calculating the monthly deviation from the average freight rate over the period. The average freight rates for VLCC, Suezmax and Aframax during the observation period are 34 140$/day, 25 415$/day and 20 004$/day respectively.

The data set was created by manually inserting monthly ship- and market specific observations for each of the 2079 operational ships over the observation period of 48 months. If the ship was scrapped, observations stop after the month of scrapping. For ships built during the period, observations start from January that year. The data structure is displayed in figure 3.1, exemplified by the two vessels Andhika and Sola TS with belonging ship characteristics and market data.

Table 3.1 – The data structure

ID	Name	DWT	Age	Year Built	Scrapped	Month	Month no.	Year	BP	OP	SP	LIBOR	FR	FR Dev.	Del.	Del.Dev.
888	Andhika	149849	25	1991	0	Sep.16	25	2016	242	48.5	292	1.32	21350	-15.9%	7	4.4
888	Andhika	149849	25	1991	0	Okt.16	26	2016	265	50.1	285	1.32	21750	-14.4%	2	-0.6
888	Andhika	149849	25	1991	0	Nov.16	27	2016	252	48.5	280	1.32	22500	-11.5%	3	0.38
888	Andhika	149849	25	1991	1	Dec.16	28	2016	296	56.7	292	1.32	22500	-11.5%	2	-0.63
643	Sola TS	113737	0	2017	0	Nov.17	39	2017	353	63.8	405	1.34	15125	-24.4%	3	-1.06
643	Sola TS	113737	0	2017	0	Dec.17	40	2017	346	66.4	435	1.34	15250	-23.8%	0	-4.06
643	Sola TS	113737	1	2017	0	Jan.18	41	2018	371	70.5	450	1.35	15125	-24.4%	7	2.94
643	Sola TS	113737	1	2017	0	Feb.18	42	2018	356	65.1	448	1.36	15000	-25.0%	4	-0.06

BP: Bunker Price. OP: Oil Price. SP: Scrap Price. FR: Freight Rate. Dev: Deviation. Del: Deliveries

Source: (Clarksons Shipping Intelligence Network, 2018, Clarksons World Fleet Register, 2018)

In table 3.2 the descriptive statistics of the crude oil tanker fleet is shown as of 01.01 each year and scrapping numbers over the the course of the year. Our scrapping observations in 2018 end at 01.09, when the data was collected. The years 2014, 2015 and 2016 are characterized by few demolitions as only 24 of 155 ships were scrapped in these years, the remaining in 2017 and 2018. There were no losses due to accidents during the observation period.

The number of deliveries increase after 2015 where 309 of 379 ships were delivered from 2016 to 2018. The descriptive statistics show an increase in fleet supply in deadweight tonnes and number of ships in all segments every year, except for Aframax from 2014 to

2015. The high number of new ships in the market the past three years is likely caused by excessive contracting of new ships during the market upturn.

A variable for the number of deliveries in each segment for each month is added to include the effect of increased supply of vessels to the market. The tanker fleet grew from 609, 457 and 635 to 732, 540 and 706 vessels for the three segments VLCC, Suezmax and Aframax respectively, during the observation period. A growth of 20,20%, 18,16% and 11,12%. To be able to compare across segments when pooling the data we calculated the deviation from average deliveries per month in percentage.

Due to few deliveries and little scrapping in the first years, the average age of ships in all three segments increase by approximately 1,5 years from 2014 to 2016. This development slows down after 2016 when scrapping activity increase. From 2017 to 2018 the average age of Suezmax decreases.

This study will be limited to crude oil tankers operating worldwide. We excluded the smallest segment of Panamax vessels because they are mostly used as product tankers. We will not take any environmental or ethical considerations regarding where the scrapping is done, but rather focus on the determinants behind the scrapping decision. When a ship is scrapped, the shipowner has taken an individual stance in relation to ethical and environmental issues through the manner and the place the ship is demolished.

We expect to find, in accordance with previous research, that age is a highly significant factor across all segments during any market situation. We expect that freight rate is a significant market variable, because it shows how much revenues shipowners generate and it reflects the company's financial situation through the value of the assets. A higher freight rate will increase a shipowner's willingness to keep a ship operational, despite higher age and costs. Lastly, we expect that scrap price is significant and positively correlated with scrapping.

Table 3.2 – Descriptive statistics

2014	**VLCC**	**Suezmax**	**Aframax**
Total Fleet (no.)	609	457	635
Total Fleet (dwt)	187 004 136	71 189 050	68 852 035
Deliveries	24	8	4
Scrapped	1	2	7
Proportion scrapped	0,16 %	0,43 %	1,10 %
Ave age of fleet	8,08	8,32	9,53
Max age of fleet	25	35	37
Min age of fleet	0	0	0
Ave age scrap	19	20,5	23,71
Max scrap age	19	21	31
Min scrap age	19	20	19
Average size (dwt)	307 068	155 789	107 741
2015			
Total Fleet (no.)	632	463	632
Total Fleet (dwt)	194 316 043	72 441 814	68 198 419
Deliveries	20	10	4
Scrapped	2	0	3
Proportion scrapped	0,32 %	-	0,47 %
Ave age of fleet	8,76	9,12	10,31
Max age of fleet	26	36	38
Min age of fleet	0	0	0
Ave age scrap	24,5	-	23,00
Max scrap age	26	-	23
Min scrap age	23	-	23
Average size (dwt)	307 462	155 806	107 909
2016			
Total Fleet (no.)	650	473	655
Total Fleet (dwt)	200 547 282	73 696 459	68 371 537
Deliveries	47	25	22
Scrapped	2	1	6
Proportion scrapped	0,31 %	0,21 %	0,92 %
Ave age of fleet	9,44	9,93	11,18
Max age of fleet	23	37	39
Min age of fleet	0	0	0
Ave age scrap	18,5	25	25,33
Max scrap age	22	25	38
Min scrap age	15	25	18
Average size (dwt)	307 704	155 852	108 012
2017			
Total Fleet (no.)	695	497	684
Total Fleet (dwt)	214 337 464	77 614 266	70 197 494
Deliveries	50	56	32
Scrapped	13	13	28
Proportion scrapped	1,87 %	2,62 %	4,09 %
Ave age of fleet	9,77	10,40	11,67
Max age of fleet	24	38	40
Min age of fleet	0	0	0
Ave age scrap	21,77	21,92	21,07
Max scrap age	24	25	27
Min scrap age	18	18	17
Average size (dwt)	307 354	155 873	108 163
2018			
Total Fleet (no.)	732	540	706
Total Fleet (dwt)	229 028 577	86 197 738	70 964 532
Deliveries	26	27	24
Scrapped	30	17	30
Proportion scrapped	4,10 %	3,15 %	4,25 %
Ave age of fleet	9,87	10,04	11,70
Max age of fleet	25	39	41
Min age of fleet	0	0	0
Ave age scrap	19,30	22,00	21,33
Max scrap age	25	39	41
Min scrap age	17	20	15
Average size (dwt)	307 634	155 942	108 675

3.2. Methodology

Logistic regression is a suited analysis for modelling binary outcomes. The response variable can take the value 1 for success or 0 for an unsuccessful occurrence of an event. In our case the outcome involves the decision of either scrapping (1) or keeping a ship in service (0). The logit model does not classify, but rather estimates probabilities for the dependent variable, on the basis of values from the explanatory variables.

$$V_{i,t} = \begin{cases} 1 \text{ if vessel is scrapped} \\ 0 \text{ if vessel is kept in service} \end{cases}$$

For vessel i at time t.

The probability of the outcome must lie between 1 and 0, but the predicted values might exceed this interval[2]. To allow for this, the probabilities are replaced with the odds of $V_{i,t}$ occurring. The odds ratio is calculated by dividing the probability of success with the probability of an unsuccessful occurrence.

$$Odds = \frac{Pr(V_{i,t} = 1)}{1 - Pr(V_{i,t} = 1)} \tag{3.1}$$

This limits the model to a lower bound, where the odds can go from zero to positive infinity. By taking the natural logarithm of the odds ratio, the model is not restricted to a lower bound and the probabilities can vary from negative infinity to positive infinity (Menard, 1995, p. 12).

$$Logit\ Odds = ln\left(\frac{Pr(V_{i,t} = 1)}{1 - Pr(V_{i,t} = 1)}\right) \tag{3.2}$$

This is called the logit of $V_{i,t}$. Using the logit of $V_{i,t}$ as the dependent variable, the problem of estimated probabilities exceeding 1 and 0 is no longer present. It is important to note that using probabilities, logit of $V_{i,t}$ and the odds is the exact same thing, only modified to allow the estimators to take on values outside the zero to one interval (Menard, 1995, p. 13).

[2] The probabilities will get close to 0 and 1, as the variables move towards positive- and negative infinity, but never reach the binary values. $\lim_{x\to\infty} Vi = 1\ and\ \lim_{x\to-\infty} Vi = 0\ (Tufte,\ 2000)$.

3.2.1 Estimating and assessing the model

Estimating the coefficients in the logit model is different from linear regression like Ordinary Least Square (OLS), which minimizes the sum of squared residuals. Instead, maximum likelihood estimation is used on the log likelihood function. The goal is to maximize the likelihood of obtaining the observed outcome of V, given the values of the dependent and explanatory variables (Menard, 1995). This is done in an iterate way where the model is revised until the best fit is obtained.

$$log(Pr(V_{i,t} = 1|\Omega)) = \sum [V_{i,t}\ log(-\boldsymbol{x_i\beta}) + (1 -\ V_{i,t})\ log\ (1 - F(-\boldsymbol{x_i\beta}))] \tag{3.3}$$

The defined maximum likelihood function is displayed in equation 3.3, where $\mathbf{x}$ is the matrix of explanatory variables for vessel i, and $\boldsymbol{\beta}$ is the vector of coefficients (Gourieroux, 2000). The cumulative density function[3] is assumed to be logistic distributed where $F(x) = \frac{1}{1+e^{-x}}$. The distribution is symmetric with zero mean as $F(-x) = 1 - F(x)$, or in our model: $F(-\boldsymbol{x_i\beta}) = 1 - Pr(\,V_{i,t} = 1 \mid \boldsymbol{x_i\beta})$ (Gourieroux, 2000, p. 11-12)

The logit model also differs in the goodness of fit measure, compared to OLS. R^2 measures in OLS how much of the variation in the dependent variable, the set of explanatory variables account for. In the logit model, McFadden Pseudo R^2 is used as a goodness of fit measure. It is based on the iterations of the maximum likelihood function where it compares the restricted model with no explanatory variables to the unrestricted model including a full set of explanatory variables[4]. The McFadden R^2 varies from 0 to 1 where higher values are associated with better predictive power (Hu et al., 2006).

To further assess the models, the significance of the coefficients are tested. For a single explanatory variable the z test is used. When testing for several explanatory variables and the overall relevance of a model, the Wald test is preferred. This is comparable to the F-test for joint significance in OLS. A low p-value of the Wald test is associated with rejecting the null hypothesis that none of the coefficients are significant (Bruin, 2011).

[3] With an S shaped curve between 0 and 1.

[4] McFadden R^2 is defined as 1- $\frac{logL_{\mathrm{UR}}}{logL_{\mathrm{R}}}$. R: Restricted mode. UR: Unrestricted model

Interpretation of coefficients

A positive coefficient reflects a positive relationship between the increase of a variable and the log odds, hence the probability of the binary outcome. The same applies for negative coefficients. For the decision to scrap a vessel, a positive coefficient is therefore associated with an increase in the scrapping probability (Tufte, 2000).

3.2.2 Model specification and assumptions

Collinearity and bias

When analyzing the tanker market and the probability of scrapping a vessel, multiple variables were considered to increase predictive power. However, the problem of collinearity between several of the explanatory variables have been an issue.

Including a variable that is correlated with the other explanatory variables inflate the standard errors and affect inference. Omitting a relevant variable increase the risk of biased coefficients. It impacts the model more if the omitted variable is highly correlated with the included variable (Menard, 1995). Collinearity is easy to detect, but there are few solutions to it. The dilemma is that by removing the correlated variables might lead to biased coefficients, while keeping them inflates variance.

This tradeoff is therefore important when specifying our models. Correlation above 0.8 will likely cause problems, but above 0.9 will almost certainly result in insignificant coefficients (Menard, 1995, p.66). While high correlation is bad, biased estimates is regarded as a more serious problem than inefficiency. Nevertheless, according to Menard (1995) small amounts of bias is preferred over huge inefficiency.

Linearities

In order to choose the best linear form of the explanatory variables we performed a Davidson MacKinnon test for two nested models. One with linear and one with log transformed variables. The results were inconclusive as the predicted values from both regressions were insignificant with high p-values. Also, estimated models with log transformed variables gave the same results as those with linear variables. Model specification is therefore done without log transforming the variables, in accordance with econometric principles and variables in previous research (Alizadeh et al., 2016, Yin and Fan, 2018)

3.2.3 Modelling scrapping probability in the tanker market

This thesis analyze the determinants impacting the scrapping decision in the tanker market. By looking at vessel and market specific variables we aim to reveal differences between the three segments and in the two time periods before September 2016 and after August 2016. The first model is estimating vessel specific factors of AGE and DWT for each segment.

The relationship between the dependent and the explanatory variable in the vessel specific model is shown in equation 3.4.

$$Logit(V_{i,t} = 1|\Omega) = \beta_0 + \beta_1 Age_i + \beta_2 DWT_i \tag{3.4}$$

Taking the antilog of equation 3.4 gives us the probability of scrapping vessel i in a given month t on the basis of Ω, including all vessel specific variables.

$$Pr(V_{i,t} = 1|\Omega) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 DWT_i)}} \tag{3.5}$$

Further, we examine the effect of market situation, represented in the coefficients *Freight Rate*, *Scrap Price* and *Deliveries* on the probability of scrapping a vessel. The logit model including market specific variables are reported in equation 3.6, where i is a vessel, belonging to one of the three classes, at time t. To investigate any common trends across the three segments we pool the observations, creating a logit model as in equation 3.6, only removing the segmentation of the vessels.

$$Pr(V_{i,t} = 1|\Omega) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 DWT_i + \beta_3 ScrapPrice_t + \beta_4 FreightRates_{it} + \beta_5 Deliveries_t)}} \tag{3.6}$$

When estimating differences prior to- and after August 2016 model 3.6 still applies, but with t varying from month September 2014 to August 2016 in the first estimation and from September 2016 to August 2018 in the last.

4. Empirical Approach and Analysis

4.1. Outline of the analysis

The objective of the analysis is to get an overview of which factors are significant when a tanker is scrapped. The analysis is divided into four parts:

1. Estimate the impact of vessel specific factors of age and size on scrapping, within each segment.

2. Compare the effect of market situation on scrapping probability between the three segments.

3. Pool all segments into one and look at common trends.

4. Divide the pooled data and look at the two periods from September 2014 to August 2016, and from September 2016 to August 2018, to see how the market has changed, impacting the coefficients and their sign and significance.

4.2. Vessel specific factors

First, we estimate how much the vessel specific factors impact the decision to scrap in a simple logit model for each of the three tanker segments over the observation period. The logit model estimate the probabilities of a ship being scrapped on the basis of the explanatory variables AGE and DWT. The binary variable $\mathrm{V}_{i,t}$ takes the value 1 if a vessel was scrapped and 0 if it was kept in service in a given month. Over the 48 months analyzed, 48 VLCC, 33 Suezmax and 74 Aframax vessels were scrapped. As explained before, only a small part of the scrapping activity happened before 2017.

Estimation results of vessel specific factors for all classes are reported in table 4.1. As expected the coefficient of AGE is strongly significant and the probability of scrapping a vessel increase with age across all segments. The largest coefficient for age is seen in the Suezmax segment. This is also the only segment where DWT is significant for scrapping probability. A positive sign of the size coefficient indicates that larger vessels have a higher probability of being scrapped. This might be because shipowners want to reduce supply and increase rates. Larger vessels are also less flexible and may operate in a limited number of ports and in a market downturn unit loads are often smaller, possibly explaining the coefficient.

The vessel specific model explain a fair part of the variation in scrapping activity with McFadden R^2 values of 29.3%, 25.5% and 22.5% for VLCC, Suezmax and Aframax respectively. Similar to the research of Alizadeh et al. (2016) the predictability for smaller vessels tends to be lower than for larger ones. Given the Wald test statistics, we reject that the coefficients simultaneously are equal to zero.

Table 4.1 – Impact of vessel specific characteristics on scrapping probability for the three tanker segments 2014-2018

	(1)	(2)	(3)
VARIABLES	VLCC	Suezmax	Aframax
AGE	0.492***	0.581***	0.397***
	(0.036)	(0.160)	(0.098)
DWT	-0.062	0.696**	-0.137
	(0.113)	(0.349)	(0.488)
Constant	-12.397***	-27.976***	-11.762*
	(3.776)	(6.334)	(6.748)
Observations	33,480	24,585	31,340
Number of Vessels	775	583	721
McFadden R^2	0.293	0.255	0.225
Wald test statistics	269	15	53
P-value	[0.000]	[0.000]	[0.000]

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

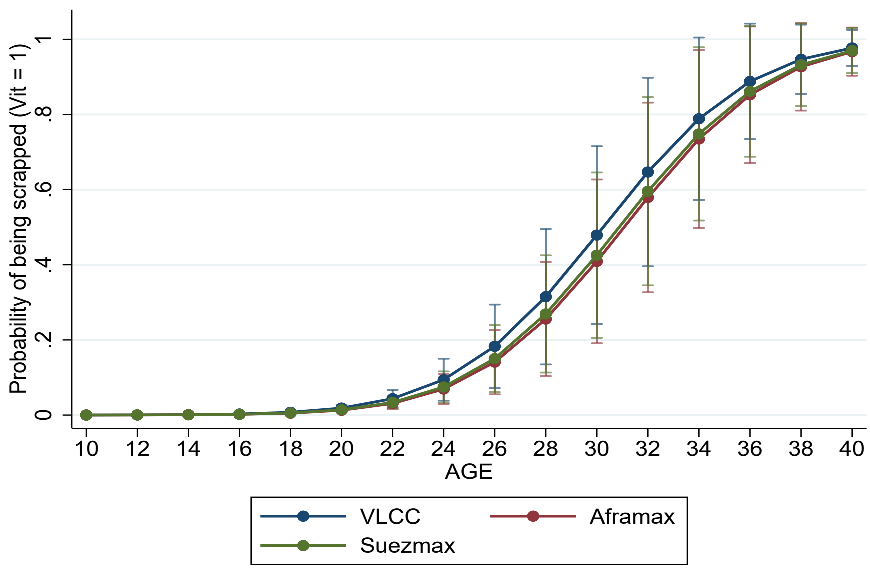
To visualize how scrapping probability develops with age, we plot the marginal effects of age on the probability of scrapping, from age 10 to 40[1]. According to figure 4.1, we see that an increase in age up until 22 years has a relatively low impact on the scrapping probability for all vessels. From 22 years and onward there is a steep increase and age has a bigger impact on the scrapping decision. For example, at age 30 there is a 50% probability of being scrapped for a VLCC, while closer to 40% for a Suez- and Aframax.

[1]The oldest vessel in the VLCC fleet is only 26 years of age and the marginal effects beyond this is predicted. VLCC marginal effects from age 10 to 26 are reported in appendix figure 6.1

The higher marginal probability of being scrapped for VLCCs than Suez- and Aframax vessels, as age increase, is as expected. The oldest scrapped VLCC was 26 years, compared to 39 for Suezmax and 41 for Aframax. Also, the age profile of the vessels show that the VLCCs are the youngest in the data set, implying that vessels in this segment are scrapped at a lower age. A median age of 8 for VLCCs, compared to 10 for Aframax, along with the lowest average age of scrapped vessels supports this result.

A possible explanation to this is the increased scrapping levels due to freight market conditions in our observation period, seen in figure 1.1. As earnings decrease and scrapping activity increase, younger VLCC vessels are scrapped. This is consistent with previous research from Abouarghoub and Mariscal (2011) stating that larger vessels are more exposed to freight market volatility compared to smaller ones. These findings are also in line with Alizadeh et al. (2016) where the largest dry bulk carriers have a higher probability of being scrapped, due to old age, than smaller ones.

Figure 4.1 – Marginal effects of age on scrapping probability



4.3. Market specific factors

To account for the impact of market situation on the scrapping decision, we extend the analysis to include several market variables. The estimated results are shown in appendix table 6.1. Other than age and size, market variables for oil price, scrap price, freight rate, interest rate and deliveries are included. *Bunker cost* is removed from the estimation due to the almost perfect correlation with oil price[2]. The coefficient of AGE is still significant for all classes. However, the market variables seem to impact the three segments differently and the sign and significance of the coefficients are not fully as expected. To examine whether any of the variables are too closely correlated, causing inflated standard errors due to multicollinearity, we estimate a correlation matrix shown in table 4.2.

From correlation plot 4.2, we see a strong positive correlation between *Scrap Price* and *Oil Price* and a strong negative correlation between *Monthly Libor* and *Freight rates.* According to Menard (1995), removing a relevant variable that is correlated with another explanatory variable reduces the inefficiency but might cause biased estimates. However, small amounts of bias is preferred over huge inefficiencies. To improve the model, we therefore opt to remove two of these highly correlated coefficients.

In the tanker market the oil price and its development impact both the operating costs of tanker owners, as well as being an important revenue driver. It also directly affects the price of the commodity the ships are carrying. However, scrap price is the monetary value shipowners receive per tonne of scrapped steel and is in estimation 6.1 more significant in explaining scrapping behaviour than oil price. Since time charter freight rates are used, bunker cost is the charterers responsibility, further decreasing the importance of the oil price variable. Additionally, according to previous research, (Alizadeh et al., 2016, Knapp et al., 2008) scrap price is a preferred variable to estimate scrapping probability.

Furthermore, interest rates[3] and freight rates[4] are also significant in previous research. Monthly Libor is an approximation of the opportunity cost of employing capital elsewhere,

[2]See correlation plot in figure 4.2

[3]Alizadeh et al. (2016)

[4]Alizadeh et al. (2016), Knapp et al. (2008), Yin and Fan (2018)

as well as impacting capital expenditure for shipowners. Nevertheless, freight rate is the direct revenue shipowners receive from employing their tankers in the market and the main determinant of profitability.

To avoid inefficient estimates, we therefore choose to remove the two variables *Oil Price* and *Monthly Libor* from our logit model, resulting in table 4.3. These results are based on variables proven to give predictive power in earlier studies and are more consistent with our expected findings.

Table 4.2 – Correlation matrix of all explanatory variables

Variables	AGE	DWT	SP	OP	BC	FR	DV	ML
AGE	1.000							
DWT	-0.282	1.000						
Scrap Price (SP)	-0.000	0.004	1.000					
Oil Price (OP)	-0.001	0.006	0.863	1.000				
Bunker Cost (BC)	-0.000	0.004	0.865	0.973	1.000			
Freight Rate (FR)	-0.046	-0.001	-0.500	-0.563	-0.615	1.000		
Deliveries (DV)	0.024	-0.003	-0.235	-0.126	-0.102	-0.251	1.000	
Monthly Libor (ML)	0.065	0.005	0.294	0.359	0.358	-0.827	0.244	1.000

From estimation results reported in table 4.3, *AGE* is still significant across all segments. The coefficients of *Scrap Price* and *Freight Rate* are significant at a 1 percent level for all segments, showing the importance of market situation on scrapping probability. This is also consistent with Buxton (1991) arguing that shipowners scrap vessels due to freight - and recycling market conditions. The negative coefficient of *Freight Rate* is interpreted as an increase in earnings, lowers the probability of scrapping. This seems reasonable since shipowners receive higher revenues from ships while they are in operation, decreasing willingness to scrap.

An increase in *Scrap Price* is associated with higher scrapping probability. This is as expected and according to theory as higher scrap prices result in higher scrap value shipowners receive when demolishing a vessel.

Another explanation of the significant and positive coefficient of *Scrap Price* is the negative correlation between the demolition- and freight market in our observation period.

Table 4.3 – Estimation results of vessel and market specific factors on the VLCC, Suezmax and Aframax segment from 2014-2018

	(1)	(2)	(3)
VARIABLES	VLCC	Suezmax	Aframax
AGE	0.671***	0.810***	0.432***
	(0.109)	(0.158)	(0.060)
DWT	-0.179	0.472	-0.213
	(0.208)	(0.414)	(0.357)
Scrap Price	0.013***	0.009***	0.008***
	(0.004)	(0.003)	(0.002)
Freight Rate	-0.139***	-0.354***	-0.230***
	(0.048)	(0.109)	(0.059)
Deliveries	0.045	-0.531***	0.007
	(0.079)	(0.119)	(0.064)
Constant	-14.664*	-25.759***	-11.042**
	(8.045)	(7.490)	(5.096)
Observations	33,480	24,585	31,340
Number of Vessels	775	583	721
McFadden R^2	0.376	0.388	0.291
Wald test statistics	47	50	109
P-value	[0.000]	[0.000]	[0.000]

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A higher scrap price is according to Karlis and Polemis (2016), associated with lower freight rates and thereby higher scrapping probability. Furthermore, according to Dixit and Pindyck (1994), scrapping can be viewed as an investment, both in future freight rates as supply decreases, and in the cash generated from sending a vessel to be demolished. However, scrapping a functioning vessel turns the value of that vessels remaining operational lifetime negative. A higher scrap price limits this negative value, as well as improving cash flow of the remaining fleet.

The predictive quality of the models represented in McFadden R^2, has increased for all segments when including market variables. This is in line with what we expected, that market situation is important in explaining scrapping activity. Relatively strong R^2 at 37.6% and 38.8% for VLCC and Suezmax, and slightly lower at 29.1% for Aframax supports the research of Abouarghoub and Mariscal (2011), stating that smaller vessels are less exposed to market volatility. Similar results, with a lower R^2 for the smaller segments, were also found for dry bulk carriers in the research by Alizadeh et al. (2016). It is also in line with our theory regarding marginal effects of age on VLCC scrapping probability where we hypothesized that freight market conditions lead to the demolition of younger VLCCs.

Following significant coefficients for age, scrap price and freight rate, deliveries are significant for the Suezmax vessel class. A negative sign translates to an increase in delivered vessels decrease the probability of scrapping. This is contraintuitive as an increase in the supply of ships would decrease profits in the future. However, in strong markets shipowners order new ships without scrapping older ones, resulting in a negative sign of the coefficient.

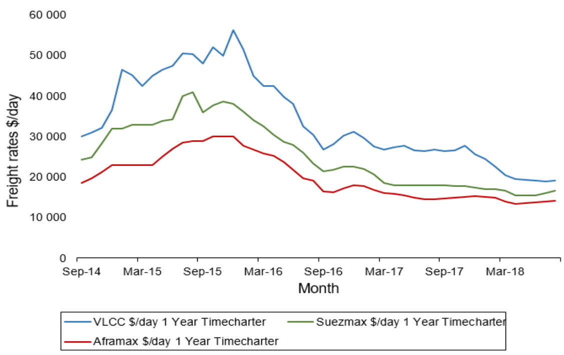
4.4. Pooled estimates

To increase the number of observed outcomes of scrapped vessels, $V_{i,t} = 1$, we pool the vessel classes and look at vessel specific and market variables over the observation period.

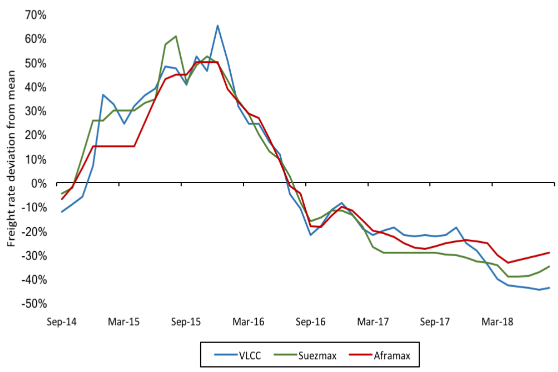
One problem that arises when pooling the data is the relative significance of freight rates. Figure 4.2 (a) show how the freight rates differ between the three segments. VLCC have the highest earnings and Aframax the lowest. The correlation between size and freight rate are shown in appendix table 6.2 and confirms this relationship between the two variables.

Figure 4.2 – Freight rate development measured in \$/day and deviation in percentage.

(a) Freight rate across segments.



(b) Freight rate deviation from mean.



To deal with this discrepancy, the deviation from average freight rate during the observation period is calculated in percentage for each segment. By using this rather than the freight rate in \$/day, we are able to compare the freight rates across the three segments. As shown in figure 4.2 (b), each segment's deviation from average freight rates follow each other closely over time, showing that the same market conditions are applicable for for all segments.

In table 4.4, we see the estimated results from the pooled model with two vessel- and three market specific variables. We get highly significant coefficients for all variables except for *DWT* and *Deliveries*. From the descriptive statistics in table 3.2, we see a small increase in average size across all segments over our observation period. This is a result of scrapping smaller ships and building larger ones, but it does not affect the model

Table 4.4 – Estimation results of pooled data from 2014-2018

VARIABLES	(1) All vessels
AGE	0.522***
	(0.042)
DWT	-0.001
	(0.014)
Scrap Price	0.010***
	(0.002)
Freight Rate	-4.881***
	(0.879)
Deliveries	-0.129
	(0.114)
Constant	-20.892***
	(1.328)
Observations	89,401
Number of Vessels	2,079
McFadden R^2	0.322
Wald test statistics	189
P-value	[0.000]

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

enough to be significant. Similarly, deliveries being significant in the Suezmax segment, but not enough to affect the coefficient in the pooled data set.

Furthermore, estimations in table 4.4 show that *AGE* is still significant and that an increase in vessel age increases the probability of scrapping. As expected, the coefficient for deviation from the average freight rate is highly significant. The negative coefficient of deviation from freight rate mean indicates that with rates above the mean, scrapping probability decrease. These results are expected and consistent with what we found in the analysis for each specific segment. *Scrap price* is also highly significant with a positive sign. Higher scrap prices means that shipowners receive more money from scrapping their ships, increasing their willingness to demolish their vessels. In the time of writing, scrap prices are relatively high while freight rates are low, which could explain the large increase in scrapping so far in 2018.

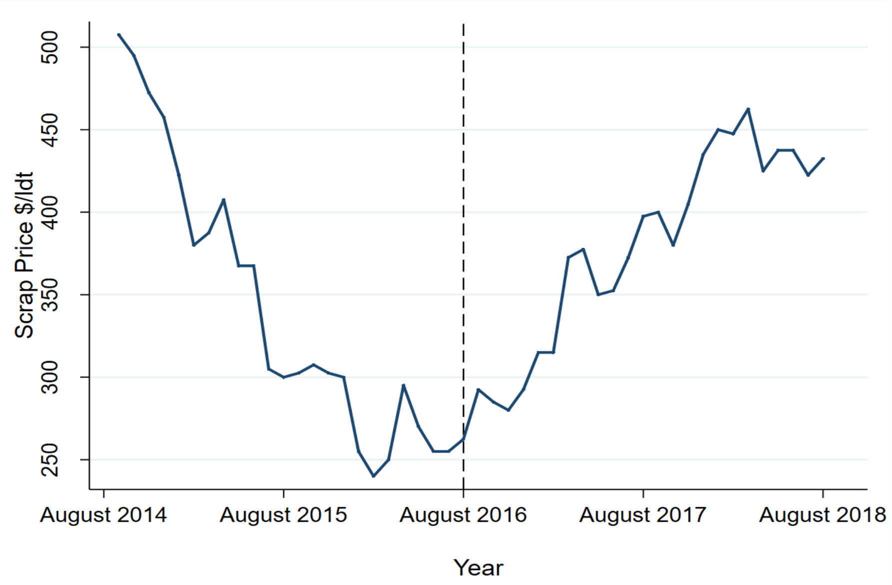
4.5. Changing market conditions

During the observation period from 2014 to 2018, the market conditions impacting the tanker industry changed. One important driver of crude oil shipping, the oil price, experienced a convex development. From the sharp increase of US shale oil production in 2014 replacing imported oil, together with lower increase in demand from China and other emerging countries, the price rapidly decreased over the following two years (World Bank Group, 2018). OPEC production cuts and increased world economic growth have since 2016 lead to an oil price increase, shown in appendix figure 6.2.

Scrap steel price follow the oil price closely and have experienced the same development the last four years. Illustrated in figure 4.3, there is a clear falling trend prior to August 2016, and increasing after. Similarly, freight rates were consistently higher across all segments during the first half of the observation period, according to table 4.5. In the first 24 months of the observation period, there was not a single month with lower average VLCC freight rates than 30 000$/day, while in the last 24 months, only two were higher.

To examine whether the determinants of scrapping behaviour is different across these two periods, we estimate one logit model *before* September 2016 and one *after* August 2016, named the first and the second period.

Figure 4.3 – Scrap price development in the observation period from 2014-2018



Due to the limited number of scrapped vessels in the first period, the model is estimated on the pooled data set to have sufficient observations. In table 4.6, the two estimated logit models for the two time periods are presented. Reported estimations show that AGE is the only significant variable explaining scrapping behaviour before September 2016. The high significance of age on scrapping probability in this period is as expected. Average age of scrapped vessels was higher in the first period, indicating that replacing old and inefficient vessels, not market situation, was an important driver behind demolition activity.

In the second period, age, scrap price and freight rate are all strongly significant. The coefficient of AGE is larger in the second half of our data period further implying that the age of a vessel is more significant after the change of market conditions. A possible reasoning behind this is that when the market conditions change and scrapping activity increases, the oldest vessels are scrapped first. These vessels were likely kept in service during the first period only due to high earnings, see table 4.5.

Scrap Price and the change from being insignificant in the first period to significant in the second period could be explained by the fact that in a good market, the scrap value of the ship is not impacting the decision to demolish a vessel. When freight rates exceed a certain point, ships are kept in service, independent of scrap price. In bad markets however, when scrapping becomes a necessary capacity reducing measure, the scrap price impacts the decision of scrapping tankers.

Table 4.5 – Freight rate averages for both observation periods and in total in $/day

	First period	Second period	Average
VLCC	43 032	25 249	34 140
Suezmax	32 473	18 356	25 415
Aframax	24 713	15 296	20 004

Furthermore, the significance of freight rates in the second period reveals an interesting point regarding market impact on scrapping probability. Namely that the freight rate is not significant in periods with high demand for shipping, but as the market decline, shipowners turn to capacity retirement to both reduce supply and remove unprofitable vessels from their fleet. The size of the coefficient also increases substantially after September 2016, indicating that an increase in freight rates after a period with low earnings, greatly decreases the scrapping probability. From figure 4.2, we see that earnings are considerably reduced after September 2016. When operating at such conditions, a freight rate increase can turn the operations from unprofitable to profitable, explaining this development.

This is further confirmed in tables 6.3-6.5 in the appendix, where marginal effects of freight rates above 35 000$/day for VLCCs and 40 000 $/day for Suez -and Aframax vessels are insignificant on scrapping probability. Meaning that in very good markets, an increase in revenues does not change the scrapping decision, because vessels are so profitable that they will be kept in service no matter what.

Table 4.6 – Estimation results of scrapping probability in the first period, before September 2016, and second period, after August 2016.

	(1)	(2)
VARIABLES	First period	Second Period
AGE	0.483***	0.615***
	(0.079)	(0.062)
DWT	-0.065	-0.001
	(0.058)	(0.019)
Scrap Price	0.005	0.019***
	(0.003)	(0.003)
Freigh rate	-1.604	-6.945***
	(1.624)	(2.421)
Deliveries	0.025	-0.176
	(0.386)	(0.125)
Constant	-18.581***	-27.633***
	(2.634)	(2.267)
Observations	42,781	46,620
Number of Vessels	1,864	2,059
McFadden R^2	0.323	0.298
Wald test statistics	115	98
P-value	[0.000]	[0.000]

Robust standard errors in parentheses

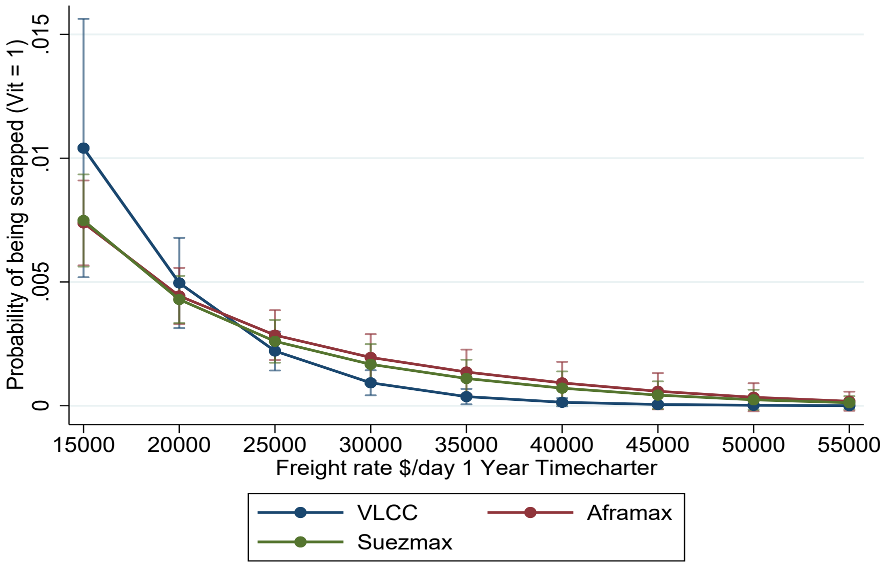
*** p<0.01, ** p<0.05, * p<0.1

Freight Rate and Delivieries are measured in deviation of average

To visualize the impact of freight rates on scrapping probability, the marginal effects are plotted in figure 4.4. Across all segments, scrapping probability is high when freight rates are low. The marginal effect is large at low freight rates, where an increase in freight rates by 5 000 \$/day is associated with several percentage points decrease in scrapping probability.

Figure 4.4 shows interesting responses to different freight rates across the segments[5]. VLCCs have a higher probability of being scrapped at freight rates below approximately 22 500 \$/day. This is as expected since VLCCs requires higher rates to break even. At freight rates above approximately 25 000\$/day, VLCCs experience lower marginal probability of being scrapped than the two other two segments. This could be due to economies of scale that this segment benefits from. Operational costs are not linear with size, resulting in higher margins for VLCCs at high rates, which again decreases the scrapping probability.

Figure 4.4 – Marginal effects of freight rates across segments



In line with Yin and Fan (2018) survival analysis of the world ship demolition market, sign and significance of the explanatory variables change with different market situations.

[5]For Suezmax and Aframax vessels freight rates above 40- and 30 000 \$/day respectively are predicted values.

In their study, increasing oil price and freight rates before 2008 gave the coefficient of bunker price a negative impact on the scrapping behaviour, while the opposite was the case with declining prices after 2008. This is consistent with our findings, where market variables in different time periods yield different results.

4.6. Limitations

Our thesis would optimally include company specific variables such as cash flow and debt to equity ratio to capture the effect of the shipowners' individual financial position. This would however require more resources and time. Further, in our model, scrapping is observed in the month of the physical scrapping. The decision to scrap itself could have been made months before, especially during strong markets, when ships are scrapped mostly due to old age. It is difficult to know exactly when the decision was made and would require input from shipowners.

A weakness in our data and our analysis are the problems we faced with correlated variables. This lead to us to exclude *Bunker Price*, *Oil Price* and *Monthly Libor* from our analysis to avoid inefficient estimates. This could impose a challenge with omitted variables bias. Furthermore, using Random Effects panel data estimations imposes strong assumptions on fixed effects. Namely, that the unobserved factors are uncorrelated with our explanatory variables.

4.7. Further research

Further and similar research is encouraged in the future to capture the effect of the IMO low sulphur regulation, enacted in October 2016, entering into force from 2020. This legislation is expected to largely affect the entire shipping industry, forcing shipowners to do major changes, possibly impacting scrapping behaviour.

The ongoing trade wars driven by China and the United States, sanctions on Iran, increasing production of shale oil and environmental agreements to reduce emission of CO2 are other factors that may affect the demand and supply for oil in the coming years, and thereby the tanker industry. These changes in market conditions will affect the shipowner's decision to scrap tankers, further encouraging an updated study in the future.

Another interesting research is an extensive analysis of the tanker demolition market over a longer observation period. This might reveal some of the shipping cycle trends and gain insight into future development of the scrapping activity of crude tankers.

5. Conclusion

The changing market conditions in the tanker market over the last four years have revealed the volatile scrapping behaviour of shipowners. From high earnings and low scrapping activity to market decline and massive capacity retirement.

In this thesis, we investigated the crude oil tanker market to determine the effect of vessel- and market specific factors on the probability of scrapping. Initially, we estimated a model including vessel specific factors such as age and size and found a strong significance of age in scrapping across all segments, in accordance with previous research. Size was positively significant for Suezmax only, indicating that shipowners have been scrapping larger vessels in this segment to decrease supply and increase flexibility.

When adding market variables such as scrap price, freight rates and deliveries to the model, predictive quality increase. This confirms the relationship between the market and scrapping behaviour. Age is still strongly significant with increased coefficients for all segments, indicating that with higher scrapping activity, older vessels are demolished first. Results show that effects on retirement of vessels are not constant across all segments. Freight rates and scrap price are significant for all three segments, while deliveries of new ships is only significant for Suezmax. When adding market variables, size is no longer a significant factor for scrapping of Suezmaxes. Also, empirical results indicate that larger vessels are more exposed to market volatility.

When pooling the three segments, findings are as expected with age, freight rates and scrap price as the only significant factors. The separate analysis of the two periods, characterized by very different market conditions, clearly shows the impact of market variations on scrapping behaviour. During times of high freight rates and falling scrap prices, age is the deciding factor. With opposite conditions, shipowners take market situation into account and choose to scrap ships to improve market conditions and reduce exposure.

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6. Appendix

Table 6.1 – Estimation results of vessel and all market specific variables

VARIABLES	(1) VLCC	(2) Suezmax	(3) Aframax
AGE	0.731***	0.823***	0.523***
	(0.126)	(0.144)	(0.068)
DWT	-2.634	4.595	-3.810
	(2.443)	(4.333)	(4.115)
Scrap Price	2.227***	2.398***	1.262***
	(0.724)	(0.793)	(0.393)
Oil Price	-0.041	-0.096***	-0.024
	(0.032)	(0.035)	(0.019)
Freight Rate	-0.004	-0.327***	-0.099
	(0.065)	(0.100)	(0.077)
Monthly Libor	1.683**	0.607	1.075**
	(0.837)	(0.724)	(0.447)
Deliveries	0.075	-0.712	-0.002
	(0.093)	(0.152)	(0.071)
Constant	-21.108**	-26.686***	-15.655***
	(9.773)	(8.106)	(5.944)
Observations	33,480	24,585	31,340
Number of Vessels	775	583	721
McFadden R^2	0.385	0.398	0.297
Wald test statistics	55	70	141
P-value	[0.000]	[0.000]	[0.000]

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 6.1 – VLCC Marginal effects plot

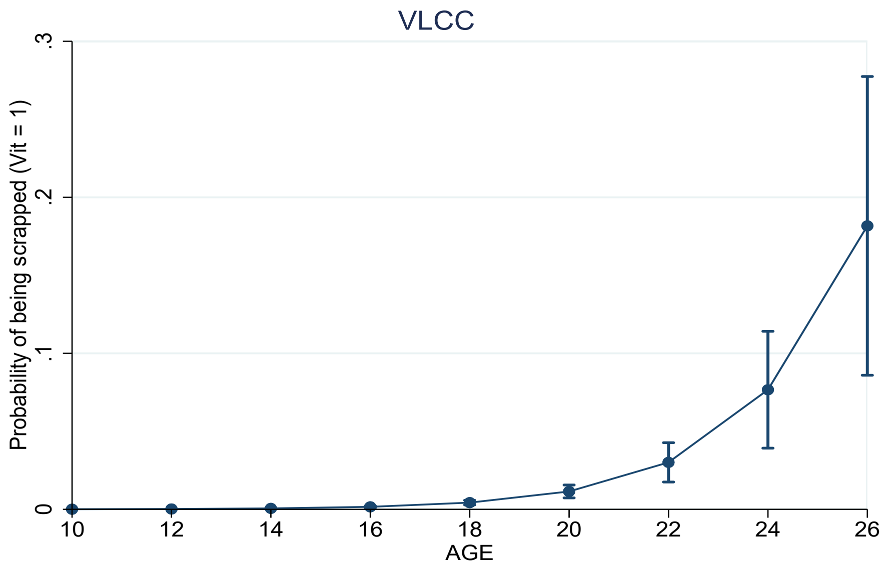

Table 6.2 – Correlation matrix of size and freight rate

Variables	DWT	Freight Rate	Deviation
DWT	1.000		
Freight Rate	0.795	1.000	
Deviation from Freight Rate	0.035	0.606	1.000

Figure 6.2 – Oil Price Development

Table 6.3 – Marginal effects table VLCC freight rates

Freight Rate	Segment	Marginal effect	Std. Err.	Z-statistics	P-value
15000	VLCC	.0113753	.0029583	31107	0.000 ***
20000	VLCC	.0053028	.0010242	43221	0.000 ***
25000	VLCC	.0022993	.0004352	46874	0.000 ***
30000	VLCC	.0009343	.000269	17227	0.001 ***
35000	VLCC	.0003596	.000159	46054	0.024 **
40000	VLCC	.0001327	.0000822	22282	0.107
45000	VLCC	.0000476	.0000384	45292	0.215
50000	VLCC	.0000168	.0000167	1.000	0.315
55000	VLCC	5.86e-06	6.95e-06	0.840	0.399

Table 6.4 – Marginal effects table Suezmax freight rates

Freight Rate	Segment	Marginal effect	Std. Err.	Z-statistics	P-value
15000	Suezmax	.0076413	.0008782	25781	0.000 ***
20000	Suezmax	.0043054	.000468	44075	0.000 ***
25000	Suezmax	.0025771	.0004392	31898	0.000 ***
30000	Suezmax	.0016418	.0004121	35855	0.000 ***
35000	Suezmax	.0010701	.0003823	29252	0.005 ***
40000	Suezmax	.0006768	.0003386	2.000	0.046 **
45000	Suezmax	.0003993	.0002724	17168	0.143
50000	Suezmax	.0002152	.0001935	43405	0.266
55000	Suezmax	.0001053	.0001205	0.870	0.382

Table 6.5 – Marginal effects table Aframax freight rates

Freight Rate	Segment	Marginal effect	Std. Err.	Z-statistics	P-value
15000	Aframax	.0077428	.000894	24320	0.000 ***
20000	Aframax	.0045497	.0005884	26846	0.000 ***
25000	Aframax	.0028815	.0005134	22402	0.000 ***
30000	Aframax	.0019564	.0004734	41365	0.000 ***
35000	Aframax	.0013573	.0004579	35096	0.003 ***
40000	Aframax	.0009096	.0004323	43375	0.035 **
45000	Aframax	.0005659	.0003706	19360	0.127
50000	Aframax	.0003203	.0002796	42005	0.252
55000	Aframax	.0001638	.0001836	0.890	0.372