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Capacity Retirement in the Dry Bulk Market: A Vessel Based Logit Model

Amir H Alizadeh Cass Business School 106 Bunhill Row London EC1Y 8TZ UK a.alizadeh@city.ac.uk

Siri Pettersen Strandenes Norwegian School of Economics Helleveien 30 NOR-5045 Bergen, Norway <u>siri.strandenes@nhh.no</u>

> Helen Thanopoulou University of the Aegean Korai 2A, Chios 82100 Greece <u>hethan@aegean.gr</u>

Abstract

The paper investigates the effect of vessel specific and market variables on the probability of scrapping dry bulk ships of different sizes. Using a 2012-2015 dataset, we find that, the probability of scrapping increases with age, but that the relation between vessels size and scrapping probability varies across the different segments. That is, the scrapping probability is lower for larger vessels in size segments where there is a trend towards building larger vessels. In addition, while the relation between earnings and probability of scrapping ships is negative, bunker prices seem to only affect the scrapping rate of smaller tonnage.

Keywords: capacity retirement, scrapping probability, dry bulk market, logit, shipping crisis.

1. Introduction

The dry bulk shipping market entered a deep and lasting depression after the 2008 financial crises with extremely low freight rates for the whole of the dry bulk sector. Historically low earnings for different subsectors within the dry bulk market made it difficult for dry bulk shipping companies and ship owners to keep vessels in operation and some resorted to retiring ships through scrapping. The recurring relapse into successive depression periods over the last few years, interrupted only by modest or short-lived recoveries, relates the extent of the post-2008 shipping crisis to the crises triggered by the 1929 financial crash and later by the oil shock in the 1970s. The scrapping volume in the 1980s marked the second significant capacity retirement in the course of the last century; the first was seen in the early 1930s with lay-up climbing in both instances to a significant percentage of the fleet (Thanopoulou, 1995). However, the current shipping crisis lacks a number of typical characteristics of the previous major shipping depressions. For instance, there has not been significant lay-up activity (Alizadeh et al, 2014) or fleet reduction through scrapping, while, on the contrary, the dry bulk fleet continued to grow after 2008 (cf. Figure 1).

Excluding losses due to accidents, capacity adjustments in shipping takes mainly three forms at firm and industry level: a) in the short term the usual way is speed reduction b) in the medium-term firms resorted traditionally to lay-up, and c) in the long-term, firms resorted historically to scrapping. In the first two cases, the capacity adjustment is temporary and reversible while in the latter case it is permanent. In addition, the decision to scrap can be triggered only by a prolonged recession with no prospect of market recovery, or due to regulatory changes - as was the case with the compulsory vessel withdrawal after the Oil Pollution Act 1990 - and obsolescence. Otherwise, firms tend to keep the vessel operating or laid-up until maintenance and repair costs exceed economical levels.

In a market downturn, not all vessel size segments are affected in the same way because shipping firms operating in different sectors and sub-sectors might not be under the same financial or cash flow pressure. For many shipping firms the deciding factor for vessel retirement can be the financial situation often related to the timing of vessel acquisitions and to their financial structure. As the crisis deepens and the outlook for recovery worsens all but the financially stronger firms start coming under pressure. In this context, rational choices for firms in financial difficulty are either: a) lay-up to stop accumulating higher losses at the variable cost level including operating expenses and voyage costs, or b) to scrap vessels in order to recoup part of the invested capital when liquidity of the firm is low with capacity retirement reflecting then cash-flow pressures.

Recent research suggests that in the context of the current crisis a faster freight rate mean reversion has reduced any gain from laying-up the vessel since the related entry and reactivation costs carry more weight for shorter than for longer lay-up periods (Alizadeh et al, 2014). However, scrapping or retirement emerged again in recent years as a response to a prolonged depressed freight market, albeit not at the levels necessary to shrink supply as in previous crises (cf. Figure 1).

In this research, we utilize a logit model in order to assess the probability of a dry bulk carrier being scrapped depending on vessels' main characteristics, such as age and size, and market specific factors including freight rate level, bunker prices, interest rates, scrap prices and market volatility. As expected, the results confirm the existence of a positive relation between age and probability of scrapping a vessel across all dry bulk sub-sectors. However, the results reveal that the relation between vessel size and scrapping probability can vary across different dry bulk segments. In particular, while the state of freight market is inversely related to the probability of scrapping, higher bunker prices seem to increase the probability of scrapping smaller tonnage. Moreover, market variables such as level of interest rates, scrap values and market volatility seem to have a positive effect on probability of scrapping dry bulk carriers.

The paper is structured in five sections. Following the introduction, the second section reviews literature on capacity retirement and shipping. Section three discusses data and methodology used for this research. Estimation results are presented in the fourth section. Section 5 concludes proposing also directions of further research.

2. Literature Review: capacity retirement and shipping

Shipping is one industry where market structure along with the nature, standardization and history of employment terms and contracts, allows maximum flexibility in temporary capacity retirement. This is evident in the form of high rates of lay-up during major shipping crises in the last one hundred years of modern shipping. A higher proportion of laid-up tonnage has been observed both during lengthy shipping crises - such as the world economic and shipping depression of the 1930s - and during shorter but deeper recessions, such as those

in 1958 and the early 1980s (Thanopoulou, 1994). However, in the context of the current crisis a number of changes in the characteristics of market cyclicality, expressed through the speed of freight rate mean reversion (recovery) together with changes related to shipowner-charterer relations (Alizadeh et al, 2014), have led to lay-up rates being at historically lower levels despite the poor freight rates of recent years.

Following the seminal work on the lay-up decision by Strømme Svendsen (1956), lay-up and scrapping have been discussed together in literature as alternatives for firms during periods of low freight rates as in Dixit and Pindyck (1994)). Cockburn and Murray (1992) relate capacity retirement to scrapping when modeling the impact of market conditions on tankers. The highly cyclical character of the shipping industry adds depth to the finding - for unrelated industries - that capital retirement has an inverse relation to the business cycle (Bonleu et al, 2013). This is corroborated by the historic record of demolition activity in international cargo shipping as illustrated in Figure 1.

However, while of obvious intuitive relevance, the shipping market cycle is an essential but not exclusive parameter of the scrapping decision. In other transport industries such as airlines it has been found that "the business cycle, the costs of capital, the cost of funds, fuel costs and noise regulation" (Goolsbee, 1998, p.493) all affect the permanent retirement of aircraft. In a more recent study, Knapp et al (2008), investigate the impact of new regulation about ship recycling coming into force and explore determinants of probability for scrapping ships on the basis of a multitude of vessel, market and location specific criteria. They report a negative relation between earnings and the probability of scrapping ships, a positive relation between scrap prices and scrapping. While their analysis is quite comprehensive, its focus is on scrapping location and covers the period prior to the 2008 crisis when shipowners' seem to have changed their attitude towards capacity retirement compared to previous crises.

A strategy followed by some shipping companies - and occasionally by certain countries in the case of state-owned fleets - is the introduction of scrap-to-build schemes, where the main objective is to renew the fleet when scrap prices are relatively high and new-building prices are relatively low. For instance, in 2010 the Chinese government aimed obviously at fleet renewal and support of the national shipping and shipbuilding industries.¹ Scrap-to-build schemes are not a new practice. In the post-war period such schemes had been adopted by countries such as Italy and Japan (Odeke, 1984) the former being then much more of a maritime power and of a shipbuilding country. Subsidized scrapping schemes have been adopted also in the case of fishing fleets although in a different perspective than freight rate restoration, as in the case of Norway (Hannesson, 2004). However, while fishing sustainability was the main objective of a more recent Scottish government initiative (Curtis, 2012), the authors later assessed the commonality of both research and owner approaches between fishing and shipping. For fishing vessel owners under cash-flow pressures, "clearing" part (or all) of urgent financial obligations through vessel demolition was an option both for improving short-term liquidity as well as for longer-term capacity planning. In the absence of such scrap-to-build schemes, ship scrapping relies solely on market forces. In this context vessels may face different probabilities to scrap; and it is important to assess which categories of vessels are more obvious candidates for scrapping.

3. Data and Methodology

3.1. The econometric model

At any given time t, the decision to scrap vessel i ($V_{i,t}$) can be a function of vessel specific factors including age and size as well as market variables such as freight market conditions, expected recovery time - when the market is low - and bunker prices. Essentially, in a cyclical market, capacity retirement will tend to be temporary unless cash-flow pressures make the choice to keep the vessel untenable. Other variables which could influence a firm's decision to scrap a vessel are scrap steel prices, interest rates, market uncertainty, as well as firm's financial and cash flow situation. Interest rates, in particular, reflect the minimum opportunity cost or competing returns, while high scrap steel prices can encourage owners to retire uneconomical vessels. Hence, we write:

$$V_{i,t} = f(A_{ge_{i,t}}^{+}, D_{wt_{i}}^{+}, FR_{i,t}^{-}, BP_{t}^{+}, SP_{t}^{+}, IR_{t}^{+}, Vol_{t}^{+}, X_{i,t}^{-})$$

¹ The scheme could be added as a variable in the scrapping decision, but it was aimed at Chinese shipping companies only and on the condition that the dry-bulk vessel to be replaced was less than 23 years of age (Chiu, 2013).

where $V_{i,t}$ is a binary variable which indicates the decision to scrap vessel *i*=1 at time *t* or keep her operational *i*=0, *Age*_{i,t} is age of the vessel *i* at time *t*, *Dwt*_i is the deadweight of the vessel, while *FR*_{i,t} is freight rate for vessel *i* at time *t*, *BP*_t stands for the bunker price at time *t*, and *SP*_t denotes scrap steel price. Finally, *IR*^{*}_t is the level of interest rate at time *t*, *Vol*_t is the freight market volatility, and *X*_{i,t} as variable(s) reflecting financial situation of the firm.²

In the short-term, as shown by occasional recent transactions, demolition price can vary by more than 10% within the same period among ship-breaking yards (Chan, 2014). This is especially so when taking into account that demolition prices offered to sellers have proved in the past to decrease in the presence of many potential candidate vessels for scrap and of low scrap steel demand as the case was in the 1980s. It has been hypothesized (Beenstock and Vergottis, 1989, p.267; Strandenes, 1984) that total "scrapping is negatively influenced by the ratio of secondhand values to scrap prices". We also model the probability of a vessel being scrapped at any given time on operational earnings and operational costs as reflected in the freight rates and bunker prices, as well as on the potential effect of vessel size on the cashflow situation. Owners of larger vessels will be affected by larger operational losses if they continue to operate the vessel at freight rates below variable cost while larger fixed-costs remain unrecoverable in a major crisis like the current one. However, economies of scale and adaptation to parcel sizes required by charterers (Thanopoulou, 1998) may allow the largest units within the size segment to find employment more easily. Hence, it is not clear that the larger operational and capital costs causes larger vessels to have a higher probability of being scrapped than smaller vessels at the same age.

Although interest rates have been at their historical low levels in the last few years, nevertheless we consider inclusion of interest rates as a cost variable which can affect the cash flow of the shipping especially when vessels are financed by debt/loan. Other specific factors - such as whether the vessel has been involved in an accident with high repair costs, or even technical obsolescence - can also affect the decision to scrap the vessel. However, with the impressively declining number of total losses – including constructive ones - in the last ten years (Allianz, 2015), this difficult to capture sporadic effect is considered too negligible

² Since financial situation of shipping firms are generally related to the shipping market condition which is reflected in freight rate and bunker prices, and due to unavailability of such information for all shipping firms we do not consider firm specific variables in our analysis and model.

to be a candidate variable. In addition, while the level of maintenance of a vessel can influence the economic life and the probability of the vessel being scrapped, we do not consider this factor due to the difficulty in having information for each vessel in the sample.

Since the dependent variable is a binary one, in order to investigate the impact of vessel specific factors on the decision to scrap, we specify and estimate a logit model for each year of the sample and each class of dry bulk market. The annual logit model is only based on vessel specific variables (age and size) which is specified in the following form:

$$\Pr(v_{i,t} = 1 \mid \Omega_t) = \frac{1}{(1 + e^{-(\beta_0 + \beta_1 A g e_i + \beta_2 D w t_i)})}$$
(2)

where $Pr(v_i = 1 | \Omega)$ is the probability of vessel *i* sold for scrapping in a given year in the sample, considering the information set Ω which includes all vessel specific variables. The logit function ensures that the probabilities vary between 0 and 1, while sign and significance of the variables can be tested once the model is estimated using an appropriate estimation method. The parameters of equation

(2) can be estimated by maximizing its log-likelihood function, which is defined as:

$$\log l\left(\Pr(v_{i,t}=1|\Omega_t)\right) = \sum v_{i,t} \log\left(1 - F(-\mathbf{x}'_i \boldsymbol{\beta})\right) + (1 - v_{i,t}) \log\left(F(-\mathbf{x}'_i \boldsymbol{\beta})\right)$$
(3)

where $F(-\mathbf{x}_i'\mathbf{\beta}) = 1 - (\Pr(v_i = 1 | \mathbf{x}_i, \mathbf{\beta}))$ is the cumulative distribution function of residuals, \mathbf{x}_i is the matrix of explanatory variables, and $\mathbf{\beta}$ is the vector of coefficients.

Furthermore, we extend the analysis by specifying a panel logit model by pooling the four year (2012- 2015) data and estimating one unbalanced panel logit regression for each subsector of the dry bulk market. The panel logit models includes market variables along vessel

specific variables including the freight market, bunker prices, scrap steel price, market volatility and interest rates.³

$$\Pr(v_{i,t} = 1 \mid \Omega_t) = 1 / (1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 Dwt_i + \beta_3 DFRi_{,t} + \beta_4 DBPt_{,t} + \beta_5 DSCt_{,t} + \beta_7 DIRt_{,t})})$$
(4)

where subscript *t* represents the year of scrapping (t=2012...2015). *DFR*_t denotes the deviation of 1 year time-charter rate (as revenue indicator) in year *t* from the long-run average of 1-year time-charter rate, *DBP*_t is the deviation of bunker price in year *t* from the long-run average bunker price used as cost indicator in the model, *DSC*_t is the difference between scrap price at time t and long run average of scrap prices, *Vol*_t is the volatility of freight market at time t, and DIR is the deviation of interest rate at time t and its long run average.⁴

3.2. Description of the dataset

The information on scrapped vessels and operational fleet in the different segments of the dry bulk market has been sourced from Clarksons Research Ltd and covers the period 2012 to 2015. The data set contains the size and age of all the vessels, as well as the date on which each vessel was scrapped. In addition, operational earnings for each type of vessel, bunker prices and scrap steel prices have been collected from Clarksons to be used as operational profitability and variable cost proxy variables. The four main segments of the dry bulk market are: a) Capesize i.e. vessels with more than 100,000 deadweight tonnes (dwt), b) Panamax (vessels of 60,000dwt to 79,999 dwt), c) Handymax/Supramax (40,000dwt to

³ It should be noted that we use the difference of freight rate, bunker prices, scrap steel price and interest rates with their long run mean value to reflect the market condition.

⁴ We estimated the volatility variable, *Vol*, using daily Baltic freight indices for different size vessels (Capesize 4TC, Panamax 4TC, Supramax 6TC and Handysize 6TC). We first estimate the volatility (standard deviation) for each day using a one year rolling sample and then calculate the average of the estimated volatilities over the year indicated in the model. For instance, we use a rolling sample of 250 observations to estimate the standard deviations for every day of 2012, and then calculate the average of standard deviations estimated for each day of 2012.

59,999 dwt), and finally d) Handysize vessels ranging from 10,000 dwt to 39,999 dwt in size.⁵

The Capesize fleet is employed mainly in the transportation of iron ore and coal, while the Panamax fleet is used primarily in grain, coal and to some extent in iron ore transportation. The smaller bulk carriers (Supramax/Handymax and Handysize) are more flexible and are used for transportation of many different dry bulk commodities such as grain, minerals, fertilizers, etc. in various routes around the world (Stopford, 2009).

Other variables including bunker price, interest rate, and scrap price are also collected from Clarkson Shipping Intelligence Network. Bunker prices are based on Rotterdam 380cst HSFO, interest rates are 1-year Libor, while scrap prices are demolition price for bulk carriers in the Far East market. Finally, the volatility of freight market is estimated for each size dry bulk ships using daily Baltic freight indices for different size vessels (Capesize 4TC, Panamax 4TC, Supramax 6TC and Handysize 6TC). We first estimate the volatility (standard deviation) for each day using a one year rolling sample and then calculate the average of the estimated volatilities over the year indicated in the model. For instance, we use a rolling sample of 250 observations to estimate the standard deviations for every day of 2012, and then calculate the average of standard deviations estimated for each day of 2012.

The statistics of fleet size, scrapping activities and average age for these four dry bulk submarkets over the period 2012 to 2015, are reported in Table 1. It can be seen that across all vessel sizes the fleet has grown significantly between 2012 and 2015 from 1299, 1294, 2298, and 2637 for the Capesize, Panamax, Supramax/Handymax, and Handysize segments to 1723, 1874, 2934, and 3427 vessels, respectively. The growth is equivalent to respective increases of 32.6%, 44.8%, 27.7%, and 29.9% for the Capesize, Panamax, Supramax/Handymax, and Handysize sectors, despite the dire freight market conditions especially in the first two segments. While there has been a drive from investors placing orders for Ecoships to achieve better economic performance, part of the increase in fleet size is believed to be due to the overhang of the orderbook from before the 2008 financial crisis.

⁵ For the purpose of analysis in this paper we apply the main classification of the dry bulk vessels most used by the industry. However, the Capesize sector can be classified further into Very Large Ore Carriers (VLOC) which includes vessels of over 200,000 dwt, Capesizes from 100,000 to 199,999 dwt, while there exists a small fleet of vessels known as Kamsarmax with a size over 80,000 but below 100,000; however, this size class of vessels has not yet reached even the 15 years age threshold as it was introduced in the early years of the past decade.

A number of orders have been placed in recent years also on the basis of unjustified optimism about an imminent recovery and falling newbuilding prices.

The statistics in Table 1 also show the number of vessels and percentage of fleet scrapped in each segment of the dry bulk sector from 2012 to 2015. In addition, while there has been no noticeable change in the average scrapping age and in the average age of the fleet across all four different segments, it seems that the average scrapping age is lower for larger vessels compared to smaller ones in any single year and for all three years the data cover. For instance, the average scrapping age in the Capesize sector was 22.9 in 2012 and 20.9 in 2015, while in the Panamax sector the average scrapping age was 28.6 in 2012 and 23.1 in 2015. Similarly, the average scrapping age in the Handymax/Supramax sector was 26.5 in 2012 and 27.1 in 2015. In the Handysize sector, the average scrapping age was 30.1 in 2012 reducing to 28.8 in 2015. Furthermore, the percentage of vessels scrapped seems to be relatively higher in the Panamax and Handysize sectors compared to the Capesize and Handymax/Supramax sectors.

Table 2 reports the average earnings in \$ per day for different size vessels over a longer period (1985 to 2011) which includes two of the most severe dry bulk crises - in the mid-1980s and in the late 1990s - along with the average earnings during the years included in the period under investigation. As expected, average earnings decrease as the size of the For instance, average earnings for vessel gets smaller. Capesize, Panamax, Supramax/Handymax, and Handysize vessel are \$26,924, \$16,077, \$12,811 and \$10,167 per day, respectively, over the sample period 1985 to 2011. Moreover, the long run mean, volatility and the deviation from the long-run mean for bunker prices and scrap steel prices are presented in the last two columns of Table 2. In general, over the sample period (2012-2015) under investigation, bunker prices have been above their long-run mean (average over 1985 to 2011), whereas scrap steel prices have been above their long run mean from 2012 to 2014, and below the long-run mean in 2015.

4. Empirical Results and discussion

To investigate the impact of vessel specifics on the decision to scrap, we use a simple logit model to estimate the probability of a vessel being scrapped for each vessel size segment and each year in the sample, as well as a panel logit model to pool the information across different size classes and years. For each year, the number of vessels in each segment (Capesize, Panamax, Handymax/Supramax and Handysize) and the vessels which were sent for scrap during that year are used to construct the binary variable $V_{i,t}$, which takes the value of 0 if the vessel is in operation and 1 if the vessel is scrapped during that year. For instance, in 2012, the Capesize fleet included 1299 vessels out of which 71 were sent to demolition yards across 2012. The constructed dataset is used to estimate equation (2) for each dry bulk carrier size class and each year in the sample period.

Estimation results of the logit model of equation (2) for Capesize bulkers are reported in Table 3. It can be noted that the estimated parameters for age and tonnage are significant for all years, and as assumed, the probability for scrapping a Capesize vessel increases with vessel age. The latter effect is slightly stronger in the two first years of the sample compared to 2015. The average age of the vessels in the Capesize fleet differs only slightly between the years. The same is true for the average age of Capesize vessels scrapped each year. Contrary to what was expected (equation 1), however, within the size class proper, the probability of a vessel being scrapped is smaller for larger Capesizes than for smaller vessels in this segment. This could be due to the younger age of larger Capesize - rising to the Valemax type of 400,000dwt - vessels which have been delivered over the past few years.

Similarly, Table 4 reports estimation results for the scrapping probability for Panamax vessels. For this segment, the results are significant and confirm the expected sign of the parameters. Hence, the probability increases with vessel age. Within the category, it also decreases with vessel size due to the trend towards building larger vessels of this category in later years. From the scatter diagram in Figure 3 we see that there is a clear trend whereby younger Panamax vessels are larger than the older ones. Consequently, the age effect may be attributed to both the age proper and size-trend variables. The two remaining dry bulk segments, Handymax/Supramax and Handysize, present results as reported in Table 5 and Table 6, respectively.

In addition, the relatively high coefficient of determination measured by McFadden R^2 , in all estimated models indicate that the two variables of age and dwt can explain a large part of the probability of a vessel being scrapped. This is also in line with the Hosmer and Lemeshow (1989) test statistic for goodness of fit which compares the fitted expected and actual values in deciles. Moreover, the percentage gain indicators reveal that the estimated models tend to increase the predictive power of probability model significantly. For instance, in the case of

Capesizes these are calculated as 53.27%, 39.53%, 27.59%, and 34.58% for 2012, 2013, 2014 and 2015, respectively. However, for all vessel sizes, the percentage gain tends to decrease from 2012 to 2015.

To increase the efficiency of the model and reliability of the results, we also use a modified panel logit regression model, which involves construction of a panel data with two dimensions: period and vessels. To this extent, we combine the data over the 4 years and construct an unbalanced panel with a dimension of (1723x4) for the Capesize, (1874x4) for the Panamax, (2934x4) for the Handymax/Supramax and (3427x4) for the Handymax/Supramax segments. The first number indicates the fleet and the second number is the year.

In the panel data regression, we estimate the parameters across all four years, for each of the four dry bulk segments as specified in equation (4). This way we can include those variables reflecting the market condition and assess the probability for scrapping vessels in each dry bulk sub-sector. However, because the panel regression for each vessel class covers only 4 years, we can include a maximum of 2 annual variables and the constant of the regression to be able to estimate the model. Thus, we include: (1) the difference of the current freight rate relative to the long-run mean of freight rates for the earlier years, that is, relative to the mean of freight rates for 1985-2011, and (2) the current bunker price relative to its mean value for the same previous period (cf. Table 2) in the model.

The results of the panel logit regression for different size classes are reported in

Table 7. The results reveal that the estimated parameters for age and size variables are significant for all vessel segments with expected signs consistent with previous results in literature (Knapp et al., 2008). However, the parameters for the deviation of freight rates (DFR_t) and the deviation of bunker prices (DBP_t) from their respective means seem to be different across vessel sizes. Negative coefficients for the relative freight rate indicate that the probability for scrapping falls when freight rates rise above the mean level for all segments, as should be expected, although the coefficients are significant only for the Capesize and Handysize segments. In addition, significant and positive estimated parameters of deviation of fuel prices from the long-run mean for Handymax/Supramax and Handysize vessels suggest that fuel prices above the long-term mean increase the probability of vessels to be scrapped. Finally, estimated coefficients of scrap steel prices seem to be insignificant.

Again, the relatively high coefficient of determination measured by McFadden R^2 , in all estimated models indicates that vessel specific and market variable used can explain a large part of the probability of a vessel being scrapped. Estimated "percentage gain" statistics of 40.3%, 35.28%, 28.52% and 26.3% for Capesize, Panamax, Supramax and Handysize models, respectively, indicate that models tend to significantly improve the predictive power of probability of a vessel being scrapped across different size classes. However, such predictability tends to decrease for smaller vessels compared to larger ones.

Furthermore, we estimate a panel-logit model combining all vessel classes in which vessel specific and all market variables are considered. The estimation results reported in the last column of Table 7 reveal several interesting points. First, the estimated coefficient of age is positive and significant, while estimated coefficient for vessel size (β_2) is insignificant. This is mainly because the respective negative and positive effects of this variable on large and small size classes observed before seem to cancel each other. However, amongst variables reflecting market conditions, estimated coefficient of freight rate (β_3) is negative and significant as before. The estimated coefficient of bunker price (β_4) is not significant suggesting that overall bunker prices do affect the probability of a vessel to be scrapped, which can be attributed to the fact that ship-owners used slow steaming to reduce their bunker costs and avoid scrapping vessels over the period examined. Estimated coefficients for scrap prices (β_5), market volatility (β_6) and interest rates (β_7) are all positive, significant

and in line with the theory. Generally, higher scrap prices tend to encourage owners to send inefficient ships to be scrapped, while higher interest rates (Libor) can increase cost of debt for shipping loans and deteriorate the firm's cash flow position which in turn can lead to firms in difficulty to scrap ships. Finally, increase in market volatility which leads to cash flow uncertainty can affect shipping companies' survival in periods of bad market condition, increasing probability of scrapping. In addition, increase in market volatility can directly affect the recovery outlook (Alizadeh et al. 2014) and hence increase probability of capacity retirement.

Finally, we use the estimated parameters to calculate and present the probabilities for vessels being scrapped depending on the variation of underlying vessel specific and market factors as in equation 4. Figure 3 illustrates the relationship between vessels age and size for Capesize vessels assuming low, medium and high earnings compared to their long-run mean. For Capesize vessels the probability of scrapping increases with vessel age as expected and shown in Figure 3 (panels b and e). Figure 3, also presents the probability surfaces under different market conditions with respect to freight earnings and fuel prices in relation to their long-run mean. For instance, panels a, b and c present changes in probability of scrapping a Capesize vessel when bunker price is at \$500/mt, and 1 year time-charter earnings are at one standard deviation below the long run mean (\$15000/day), at the long run mean (\$27000/day) or at one standard deviation above the long-rum mean (\$39,000/day), respectively. Furthermore, panels d, e and f present changes in probability of scrapping a Capesize vessel when the freight rate is at its long-run mean and bunker prices change from \$300/mt to \$500/mt, and \$800/mt, respectively. Clearly the probability surfaces rise as the bunker price increases indicating that higher fuel prices can affect the decision to scrap ships, everything else being constant.

Similar surfaces for the other dry bulk segments are illustrated in Figures 4-6 below. Comparing the surfaces for the different segments, we furthermore see that the probability for scrapping rises more slowly for the small Handysize vessels than for the others. This of course is consistent with the significant higher maximum age for the Handysize vessels in the current fleet, (cf. Table 1). Comparing the surfaces for the different vessel sizes also indicates that smaller Capesize and Panamax vessels have a higher probability of being scrapped than larger such vessels at the same age once these vessels reach 19 - 22 years for Capesize and 21 - 25 years for Panamax vessels. Contrary to this, the Handymax/Supramax vessels' probability for being scrapped does not vary across vessel size within the group. For

Handysize vessels the opposite is true: Larger vessels within this group have a higher probability for being scrapped than smaller vessels of similar age.

Results also show the effect of different levels of bunker prices, reflecting different levels of voyage costs. The results for different bunker prices are inverse of the effect of high, average and low earnings. The differences among the segments replicate again the effects found for different levels of earnings. This symmetry may indicate that the decisive factor is earnings relative to voyage costs as approximated by bunker costs.

The results largely conform to what was expected in terms of influence of variables on probability of vessels being scrapped. However, the results and the model can be used by investors and financiers alike for investment purposes and assessment of the viability of a shipping investment project, especially when older vessels are considered. For instance, using the model one can estimate the likelihood of terminating the project by scrapping the vessel for a given set of vessel specific and market factors.

5. Conclusion

Scrapping has emerged again as a means of capacity adjustment during the current severe shipping recession, which has evolved since the financial crisis of 2008 once more due mostly to the endemic tendency to overinvest during shipping booms (Haralambides and Thanopoulou 2014). The recent deterioration of the markets, especially of the dry bulk ones, may result in an even stronger resort to this form of retirement of capacity.

In this paper we concentrated on assessing the probability of a vessel being scrapped on the basis of size and age, taking into account market variables and voyage costs as additional variables. As expected, and in line with previous research on the subject, age and vessel size are important factors in probability of a vessel being scrapped along with market forces such as deviation of freight rate from its long-run mean and excess bunker prices from their long-run mean. However, empirical results also reveal that the effect of these factors on probability of vessel retirement may not be constant within different dry bulk size classes. In fact, in the Capesize and Panamax sectors, probability of scrapping seems to decrease for larger vessels in these sectors. In the Handysize sectors the opposite is true; that is, larger vessels within this group have a higher probability for being scrapped than smaller vessels of similar age. For Handymax/Supramax vessels probability of being scrapped does not vary across vessel size

within the group. These differences reflect the dynamics of ship size within each dry bulk segment, which in turn affects the fleet and scrapping age. For instance, the trend is towards building larger vessels in the Capesize and Panamax segment, whereas the opposite trend seem to be followed in the Handysize segment.

Our investigation is of practical importance since dry bulk markets in February 2015 reached their lowest point historically as measured by earnings in the last twenty-five years only to break this negative record again for the second time as the year was coming to an end (cf. Figure 1). Given the highly volatile nature of the dry bulk market and especially of the larger segments, financiers and other external investors can evaluate the likelihood that the fleet they are investing in may be scrapped based on vessel specific and market factors through the proposed model.

Future investigation on assessing probability of scrapping dry bulk ships can consider other vessel specific factors such as quality of build - by distinguishing the country and shipyard where the vessel is built - as well as other factors such as the level of maintenance and the magnitude of cash-flow pressures if adequate proxies can be constructed.

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	vessei cate	gory in the samp		
	Capesize	Panamax	Handymax	Handysize
2012				•
Total fleet	1299	1,294	2,298	2,637
Scrapped	71	87	78	222
Proportion scrapped	5.47%	6.72%	3.39%	8.42%
Ave age of fleet (years)	8.0	11.8	8.6	12.6
Max age fleet	31.0	35.0	37.0	54.0
Min age of fleet	1.0	1.0	1.0	1.0
Ave age scrap (years)	22.9	28.6	26.5	30.1
Max scrap age	31.0	35.0	35.0	50.0
Min scrap age	15.0	22.0	18.0	18.0
Average size (dwt)	182,982	73,047	51,832	27,223
Max size fleet	404,389	79,964	59,888	39,991
Min size fleet	100,314	60,050	40,009	10,083
2013				
Total fleet	1,482	1,412	2,628	2,972
Scrapped	44	68	80	233
Proportion scrapped	2.97%	4.82%	3.04%	7.84%
Ave age of fleet (years)	7.6	11.3	8.6	12.2
Max age fleet	31.0	39.0	38.0	55.0
Min age of fleet	1.0	1.0	1.0	1.0
Ave age scrap (years)	23.3	27.0	26.9	30.0
Max scrap age	31.0	39.0	36.0	44 0
Min scrap age	16.0	10.0	15.0	14.0
Average size (dwt)	185 617	72 998	52 216	27 793
Max size fleet	103,017	72,998	50 963	27,795
Min size fleet	404,385	60 187	39,903 AD DDD	10.036
2014	100,314	00,187	40,009	10,050
Total fleet	1 569	1 543	2 826	3 228
Scrapped	25	67	68	149
Proportion scrapped	1 59%	1 3/%	2 /1%	4 62%
Ave age of fleet (years)	79	11 2	8.8	11 3
Max age fleet	30.0	30.0	30.0	56.0
Min age of fleet	1.0	1.0	1.0	0.0
Ave age scrap (vears)	23.6	25.0	26.8	20.0
Ave age scrap (years)	25.0	23.0	20.0	29.1
Min soran ago	50.0	59.0	51.0	45.0
Average size (dwt)	10.0	10.0	10.U E2 217	15.U 20.24E
Average size (uwt)	107,574	72,024	52,517	20,545
Max size fleet	404,389	79,964	59,963	39,991
Mill size fleet	100,314	60,366	40,009	10,036
2015	1722	4074	2024	2427
Lotal field	1723	1874	2934	3427
Desception commend	92	00 4 700/	07	101
Proportion scrapped	5.34%	4.70%	2.28%	4.70%
Ave age of fleet (years)	7.78	9.41	8.93	10.93
Max age fleet	30.0	38.00	40.00	57.00
Min age of fleet	0.0	0.00	0.00	0.00
Ave age scrap (years)	20.86	23.05	27.05	28.81
Max scrap age	30.0	34.00	38.00	40.00
Min scrap age	15.0	14.00	17.00	16.00
Average size (dwt)	188,337	71,515	52,463	28,308
Max size fleet	403,844	79,964	59,963	39,991
Min size fleet	100,172	60,200	40,009	10,000

Table 1: Descriptive Statistics of age and size of the existing and scrapped fleet for each vessel category in the sample

The sample consist of vessel with different carrying capacities (deadweight dwt). The industry's classification of vessels according to size is Capesize (100,000 dwt to 410,000dwt), Panamax (60,000dwt to 79,999dwt), Handymax/Supramax (40,000dwt to 59,999 dwt) and Handysize (10,000dwt to 39,999dwt)

		Handysize	Handymax	Panamax	Capesize	Bunker Price	Scrap price	Interest rate	\	ol Standard I	Deviation %)
		\$/day	\$/day	\$/day	\$/day	\$/mt	\$/ldt	%	Handysize	Handymax	Panamax	Capesize
1985-2011	Mean	10,167	12,811	16,077	26,924	193.81	222.97	4.2				
	SD %	28.0	32.0	36.7	46.0	39.9	35.1	26.9				
	SD \$	2850	4104	5906	12381	77.36	78.25					
2012	Mean	8,233	8,655	9,708	13,749	639.64	373.25	0.69	16%	23%	41%	86%
2013	Mean	8,104	8,642	10,115	15,811	594.80	369.92	0.41	14%	16%	42%	90%
2014	Mean	9,015	10,764	12,028	21,778	532.14	298.75	0.33	12%	19%	39%	102%
2015	mean	6,709	8,116	7,505	9,962	267.80	179.17	2.50	18%	18%	41%	111%
				D	eviation	from the long	g run mean					
2012		-1,934	-4,156	-6,369	-13,175	445.82	150.28	-3.58				
2013		-2,063	-4,169	-5,962	-11,113	400.98	146.94	-3.86				
2014		-1,152	-2,048	-4,049	-5,146	338.33	75.78	-3.94				
2015		-3,458	-4,695	-8,572	-16,962	73.99	-43.81	-1.76				

Table 2: Average 1 Year Time-charter rates for different size dry bulk carriers and bunker prices over the sample period

• Freight statistics are based on 1 year time-charter rates for different size vessels, bunker prices are based on Rotterdam 380cts heavy fuel oil, scrap steel prices are based on Far East scrap values in \$ per metric tonne of light displacement, and interest rate variable is monthly Libor. Volatilities are estimated using daily Baltic freight indices for different size vessels (Capesize 4TC, Panamax 4TC, Supramax 6TC and Handysize 6TC). We first estimate the volatility (standard deviation) for each day using a one year rolling sample and then calculate the average of the estimated volatilities over the year indicated in the model. For instance, we use a rolling sample of 250 observations to estimate the standard deviations for every day of 2012, and then calculate the average of standard deviations estimated for each day of 2012.

$\Pr(v_{i,t} = 1 \mid \Omega_t) = 1/(1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 Dwt_i)})$									
Variable	Coeff	2012	2013	2014	2015				
Constant	B_0	-8.510***	-10.985***	-9.574***	-4.053***				
		(-7.018)	(-7.918)	(-5.730)	(-5.216)				
Age	B_1	0.538***	0.563***	0.450****	0.350***				
		(9.725)	(8.194)	(6.183)	(11.122)				
Dwt	B_2	-2.077****	-1.424***	-1.425***	-2.302***				
		(-4.729)	(-3.421)	(-2.972)	(-6.167)				
No Obser	No Observations		1482	1569	1723				
McFado	McFadden R ²		0.567	0.484	0.500				
Log-Like	Log-Likelihood		-85.712	-66.150	-179.416				
SBI	С	0.1785	0.1305	0.0984	0.221				
LR stat	tistic	340.465	224.749	124.257	359.292				
p-v	al	[0.000]	[0.000]	[0.000]	[0.000]				
% Cor	rect	95.17	96.52	97.73	93.390				
% Inco	rrect	4.83	3.48	2.27	6.610				
Total	Gain	5.51	2.28	0.87	3.500				
Percent	t Gain	53.27	39.53	27.59	34.580				
H-L s	tat	0.806	2.428	1.879	4.934				
		[0.999]	[0.965]	[0.985]	[0.765]				

Table 3: Estimation results of the logit model for Capesize scrapping

• SBIC is the Schwartz (1978) Bayesian model selection criteria.

• LR statistic tests the joint significance of all the variables in the model.

• McFadden R² is measured as the parentage improvement of the log-likelihood of the estimated model compared with the benchmark model with no variables.

- Total Gain indicates the improvement "% Correct" from constant probability (no model) specification
- Percentage Gain indicates the percent of incorrect (default) prediction corrected by equation compared to using constant probability (no model) specification.
- H-L stat is Hosmer and Lemeshow (1989) test statistic for goodness of fit which compares the fitted expected and actual values in deciles.

$\Pr(v_{i,t} = 1 \mid \Omega_t) = 1/(1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 Dwt_i)})$								
Variable	Coeff	2012	2013	2014	2015			
Constant	B_0	-5.943	4.310	-0.241	-6.042**			
		(-1.408)	(1.079)	(-0.075)	(-2.167)			
Age	B_1	0.476***	0.257***	0.228***	0.222***			
		(9.538)	(8.857)	(10.451)	(11.057)			
Dwt	B_2	-10.346 [*]	-17.515***	-9.787**	-0.701			
		(-1.943)	(-3.244)	(-2.317)	(-0.194)			
No Observa	No Observations		1411	1543	1874			
McFadder	$1 R^2$	0.708	0.528	0.389	0.339			
Log-Likelih	ood	-93.122	-127.160	-168.374	-234.717			
SBIC		0.160541	0.19566	0.232516	0.263			
LR statist	tic	451.499	284.793	214.630	240.663			
p-val		[0.000]	[0.000]	[0.000]	[0.000]			
% Correc	ct	95.47	94.83	93.63	92.820			
% Incorre	ect	4.53	5.17	6.37	7.180			
Total Gai	in	8.01	3.87	1.94	1.770			
Percent G	ain	63.87	42.81	23.30	19.790			
H-L stat	t	1.662	5.969	9.773	21.078			
p-val		[0.990]	[0.651]	[0.281]	[0.007]			

Table 4: Estimation results of the logit model for Panamax scrapping

• SBIC is the Schwartz (1978) Bayesian model selection criteria.

• LR statistic tests the joint significance of all the variables in the model.

• McFadden R² is measured as the parentage improvement of the log-likelihood of the estimated model compared with the benchmark model with no variables.

 Total Gain indicates the improvement "% Correct" from constant probability (no model) specification

• Percentage Gain indicates the percent of incorrect (default) prediction corrected by equation compared to using constant probability (no model) specification.

• H-L stat is Hosmer and Lemeshow (1989) test statistic for goodness of fit which compares the fitted expected and actual values in deciles.

$\Pr(v_{i,t} = 1 \mid \Omega_t) = 1/(1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 Dwt_i)})$							
Variable	Coeff	2012	2013	2014	2015		
Constant	B_0	-12.622***	-7.226***	-5.004*	-4.019 [*]		
		(-4.284)	(-2.836)	(-1.758)	(-1.656)		
Age	B_1	0.345***	0.289^{***}	0.260^{***}	0.242***		
		(10.672)	(10.357)	(9.411)	(9.443)		
Dwt	B_2	6.224	-3.385	-7.504	-8.532 [*]		
		(1.150)	(-0.693)	(-1.403)	(-1.845)		
No Observ	No Observations		2628	2826	2934		
McFadde	McFadden R ²		0.502	0.462	0.450		
Log-Likeli	Log-Likelihood		-178.496	-172.604	-175.805		
SBIC		0.151017	0.14483	0.13059	0.128		
LR statis	stic	360.76	365.05	303.15	287.292		
p-val	p-val		[0.000]	[0.000]	[0.000]		
% Corre	ect	95.81	96.15	96.59	96.600		
% Incorr	ect	4.19	3.85	3.41	3.400		
Total G	ain	2.23	1.85	1.06	1.060		
Percent (Gain	34.68	32.47	23.70	23.750		
H-L sta	at	3.212	1.818	2.885	3.504		
		[0.920]	[0.986]	[0.941]	[0.899]		

Table 5: Estimation results of the logit model for Handymax/Supramax scrapping

• SBIC is the Schwartz (1978) Bayesian model selection criteria.

• LR statistic tests the joint significance of all the variables in the model.

• McFadden R² is measured as the parentage improvement of the log-likelihood of the estimated model compared with the benchmark model with no variables.

• Total Gain indicates the improvement "% Correct" from constant probability (no model) specification

• Percentage Gain indicates the percent of incorrect (default) prediction corrected by equation compared to using constant probability (no model) specification.

• H-L stat is Hosmer and Lemeshow (1989) test statistic for goodness of fit which compares the fitted expected and actual values in deciles.

	$\Pr(v_{i,t} = 1 \mid \Omega_t) = 1/(1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 Dwt_i)})$								
Variable	Coeff	2012	2013	2014	2015				
Constant	B_0	-9.827***	-9.323***	-7.856***	-9.614***				
		(-15.753)	(-18.149)	(-16.053)	(-18.860)				
Age	B_1	0.241***	0.215***	0.164***	0.174 ^{***}				
-		(14.017)	(17.184)	(17.041)	(18.735)				
Dwt	B_2	7.241***	7.668***	5.381***	11.153 ^{***}				
		(6.538)	(7.027)	(4.424)	(8.518)				
No Observ	No Observations		2872	3228	3427				
McFadd	McFadden R ²		0.428	0.326	0.381				
Log-Likel	ihood	-421.717	-466.978	-406.694	-401.846				
SBIC	2	0.328807	0.322324	0.259488	0.242				
LR stat	istic	680.11	699.69	394.18	495.311				
p-va	il 👘	[0.000]	[0.000]	[0.000] [0.000]					
% Corr	ect	89.65	89.92	92.68	93.130				
% Incor	rect	10.35	10.08	7.32	6.870				
Total G	Gain	5.07	4.37	1.49	2.090				
Percent	Gain	32.88	30.23	16.88	23.330				
H-L st	at	9.341	13.115	8.706	14.449				
		[0.314]	[0.115]	[0.368]	[0.071]				

Table 6: Estimation results of the logit model for Handysize scrapping

• SBIC is the Schwartz (1978) Bayesian model selection criteria.

• LR statistic tests the joint significance of all the variables in the model.

• McFadden R² is measured as the parentage improvement of the log-likelihood of the estimated model compared with the benchmark model with no variables.

- Total Gain indicates the improvement "% Correct" from constant probability (no model) specification
- Percentage Gain indicates the percent of incorrect (default) prediction corrected by equation compared to using constant probability (no model) specification.
- H-L stat is Hosmer and Lemeshow (1989) test statistic for goodness of fit which compares the fitted expected and actual values in deciles.

Pr(ı	$\Pr(v_{i,t} = 1 \mid \Omega_t) = 1 / (1 + e^{-(\beta_0 + \beta_1 Age_i + \beta_2 Dwt_i + \beta_3 DFRi_t + \beta_4 DBPt + \beta_5 DSCt + \beta_6 Vol_{i,t} + \beta_7 DIRt)})$								
Variable	Coeff	Capeszie	Panamax	Handymax	Handysize	All Sizes			
Constant	B_0	-8.183***	-2.018	-8.419***	-10.906	-7.747***			
		(-12.136)	(-1.043)	(-5.528)	(-23.276)	(-24.700)			
Age	B_1	0.429***	0.262***	0.282***	0.193	0.228***			
		(19.195)	(19.571)	(19.873)	(34.174)	(52.418)			
Dwt	B_2	-1.986***	-8.902***	-2.991	7.670***	-0.016			
		(-7.883)	(-3.867)	(-1.126)	(13.308)	(-0.101)			
DFR	B_3	-0.112	-0.107*	-0.167**	-0.441	-0.093			
		(-5.786)	(-1.795)	(-2.158)	(-4.519)	(-5.866)			
DBP	B_4	0.0006	0.00001	0.0015	0.0032	-0.0003			
		(0.781)	(0.017)	(2.632)	(6.123)	(-0.173)			
DSC	B_5					0.006			
						(2.178)			
Vol	B_6					1.007			
						(3.198)			
DIR	B_7					0.212			
						(1.879)			
McFadde	en R ²	0.549	0.471	0.483	0.400	0.419			
Schwarz cr	iterion	0.157	0.219	0.134	0.284	0.219			
Log likel	lihood	-416.319	-648.595	-694.503	-1716.802	-3746.381			
LR stati	stic	1013.476	1156.449	1296.446	2292.710	5392.981			
p-val	1	[0.000]	[0.000]	[0.000]	[0.000]	0.000			
% Corr	ect	95.41	93.77	96.19	91.38	93.54			
% Incor	rect	4.59	6.23	3.81	8.62	6.46			
Total G	ain	2.97	3.39	1.52	3.08	2.28			
Percentag	e Gain	39.3	35.22	28.49	26.3	26.09			
Hosmer-Leme	eshow stat	4.252	42.046	10.203	29.561	88.269			
p-val	1	[0.834]	[0.000]	[0.251]	[0.000]	[0.000]			

 Table 7: Panel logit regression results for different size dry bulk carriers

• The estimated model is specified as a panel-logit, where $V_{i,t}=0$, 1 indicates the vessel i is scrapped or in operation and t is the year (2012, 2013, 2014 and 2015).

• The total number of observations in the panel are 5563, 6123, 10,686 and 12,264, for the Capesize, Panamax, Handymax/Supramax and Handysize sectors, respectively.

- Dwt is the deadweight tonnage scaled by 100,000, DFR is the difference between 1 year TC for vessel type in year t and long term average of 1 year TC (from 1985 to 2011), DBP is the difference between bunker price in year t and long term average bunker price (from 1985 to 2011), DSC is the difference between scrap prices in year t and long run scrap prices (1985-2011), DIR_t is the level of interest rate in year t and the long run LIBOR (1985-2015), and Vol_t is the volatility of freight market in year t..
- Robust standard errors are estimated using Huber-White quasi-maximum likelihood method.
- LR statistic tests the joint significance of all the variables in the model.
- McFadden R2 is measured as the parentage improvement of the log-likelihood of the estimated model compared with the benchmark model with no variables.
- Total Gain indicates the improvement "% Correct" from constant probability (no model) specification.
- Percentage Gain indicates the percent of incorrect (default) prediction corrected by equation compared to using constant probability (no model) specification.
- Hosmer-Lemeshow (1989) test statistics of goodness-of-fit compares the fitted expected values to the actual values in deciles.



Figure 1 Bulk carrier earnings, demolition and fleet development 1990-2015(Oct)

Source: Data from Clarksons (2015)



Figure 2: Age and size distribution of different segments of the dry bulk carrier fleet in 2012 and 2015

• The industry classification of vessels according to size is Capesize (100,000 dwt to 410,000dwt), Panamax (60,000dwt to 80,000dwt), Handymax/Supramax (40,000dwt to 60,000 dwt) and Handysize (10,000dwt to 40,000dwt).



Figure 3: Probability of scrapping Capesize vessels for different age, dwt and freight rate levels

The probability of a Capesize vessel being scrapped for different bunker prices when 1 year TC earnings is at its average long run mean (\$26,924/day) d) Bunker prices at \$300/mt e) Bunker prices at \$500/mt f) Bunker prices at \$800/mt









Figure 4: Probability of scrapping Panamax vessels for different age, dwt and freight rate levels

The probability of a Panamax vessel being scrapped for different bunker prices when 1 year TC earnings is at its average long run mean (\$16,077/day)d)Bunker prices at \$300/mte) Bunker prices at \$500/mtf) Bunker prices at \$800/mt







Figure 5: Probability of scrapping Handymax/Supramax vessels for different age, dwt and freight rate levels



The probability of a Handymax vessel being scrapped for different levels of 1 Year TC earnings when bunker price is \$500/mt

The probability of a Handymax vessel being scrapped for different bunker prices when 1 year TC earnings is at its average long run mean (\$12,811/day) e) Bunker prices at \$500/mt d) Bunker prices at \$300/mt f) Bunker prices at \$800/mt





Figure 6: Probability of scrapping Handysize vessels for different age, dwt and freight rate levels

The probability of a handy size vessel being scrapped for different bunker prices when 1 year TC earnings is at its average long run mean (\$10,167/day)

