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Forecasting Stock Return Predictability of Maritime Shipping Companies: A Recursive Modelling Approach with Implications for Market-Risk Assessment

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ABSTRACT

For maritime shipping companies, stock-return volatility and predictability are not only a finance question but also an indirect signal of the health of the industry's investment cycle. Improving the accuracy of such forecasts, and quantifying the contribution of individual macroeconomic and commodity factors, therefore matters to both investors and maritime-industry stakeholders, yet remains a challenging task. This paper employs a recursive modelling approach that simulates investor behaviour to test whether macroeconomic and commodity variables help forecast the stock returns of tanker shipping companies. Methods: We follow the recursive approach of Pesaran and Timmermann (2000) and Pourkermani (2023a). A dedicated Matlab routine allows the model structure to change at every step and evaluates the out-of-sample forecasting performance of a set of eight macroeconomic and commodity regressors for five Maritime Company's companies (Frontline, Knightsbridge Tankers, Nordic American Tankers, and Teekay Corporation) benchmarked against the S&P 500. Results: Contrary to part of the prior literature, we find that permutation-based, information-criterion-selected models do not outperform a fixed model that retains all regressors; the all-variable model consistently delivers the highest net-of-cost return. Conclusion: This paper contributes to the literature by (i) applying the recursive out-of-sample forecasting framework specifically to Maritime Company's equities, (ii) explicitly accounting for transaction costs when evaluating switching strategies, and (iii) comparing statistical, Akaike, and Bayesian information criteria for model selection in this context. Research Limitation: The model uses historical macroeconomic and commodity data and does not incorporate maritime-specific operational variables such as charter rates or bunker fuel prices, which we identify as a direction for future research.

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1. Introduction

We consider a set of macroeconomic and commodity variables to forecast the one step ahead stock return. In period t the information set contain information up to and including the period t, the forecasts combine the available variables in an effective and most efficient way to work out the return. This is done by searching for the optimal forecasting model in each period over a large number of different models that includes different combinations of variables. In every step it is not clear what variables must be included in the model nor the correct parameters of the model, now the recursive approach requires that the investor in order to find the best model will search in every step over the all-possible models to find the best forecast model. As time goes the investor recursively repeats this search and as data becomes available the best model will change. We assume that in every period t the investor considers 8 variables that may be useful for making a one step ahead forecast of stock return.

$$X_{t,i} = \left[X_{t,1} X_{t,2} \ldots X_{t,8} \right] \quad (1)$$

The investor tries to choose the best model in period t by searching over all combinations of up to 8 variables. We use a linear regression model estimated by the ordinary least square (OLS) techniques therefore we estimate the relation between excess return and the 8 variables by estimating the linear regression model of the following format.

$$\hat{r}_{t+1} = \beta' X_{t,i} + \varepsilon_{t+1,i} \quad (2)$$

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ . \\ . \\ \beta_8 \end{bmatrix} \quad (3)$$

By r_t we mean the excess return which is the difference between stock return and risk free return of Treasury bill. We use OLS technique to model the changes in the natural logarithm of the stock price where r_{t+1} is the vector of the return in the natural logarithm from period 0 up to and including period t, the subscript $i = 1,2,\ldots$ is the model considered by the investor $X_{t,i}$ denote the set of regressors under model i which is subset of the set of all macroeconomic and commodity regressors the investor considers including a constant. The vector of the regressors includes a constant. In order to identify the optimal forecasting model among the large number of estimate forecasting models we use three model selection criteria in our Matlab code, adjusted R^2, Akaike Information Criterion (AIC), **Bayesian information criterion (BIC).** The definition of the model selection criteria have been taken from [1]. All these criteria aim at minimising the residual sum of squares or increasing the value. For more information refer to Pourkermani (2023a) and Zhao et al (2025).

Beyond its contribution to the empirical finance literature, the predictability of a tanker operator’s stock returns is directly relevant to the maritime engineering community. Because newbuilding orders, scrapping decisions and fleet-renewal programmes are financed against expected freight income and are highly sensitive to the cost of capital, the volatility and forecastability of a Maritime Company’s share price act as an indirect, forward-looking signal of the health of the industry’s investment cycle (Grammenos & Arkoulis, 2002; Wang, Woo, & Mileski, 2014). For engineers and asset managers involved in fleet planning, newbuilding contracting and retrofit-investment decisions, understanding how capital markets price and forecast such returns therefore provides a complementary market-risk assessment tool alongside conventional freight-rate and orderbook indicators.

1.1. Investment Strategy

Studies such as [2] and Welch and [3] creates one set of a stock return forecast for every model selection criteria, this return series will then be compared to the one month Treasury bill return to reach an investment decision. Earlier similar studies include [4], [5] and [6-7]. Later on, [8] and also [9] have listed and reviewed the articles on return predictability. Other studies such [10], [11-12], and Chen and Hong (2012) found string evidences of structural change and parameter instability for stock forecasting models. Other studies such as [13-14], and [15] have modelled changes in time series return predictability.

Within the maritime domain specifically, Grammenos and Arkoulis (2002) were among the first to show that shipping-company stock returns load significantly on global macroeconomic risk factors such as oil prices, industrial production and exchange rates, a finding echoed by Wang, Woo, and Mileski (2014), who link financial risk indicators to the operating efficiency of shipping firms across the dry bulk, tanker and container segments. More recently, Mohanty et al. (2021) model the return and risk characteristics of shipping-company stocks directly, Melas and Michail (2024) show that commodity-price movements carry predictive content for dry-bulk shipping equities, and Kamal, Chowdhury, and Hosain (2021) document the sensitivity of maritime shipping stocks to system-wide shocks such as the COVID-19 pandemic. These studies motivate our choice of macroeconomic and commodity regressors and confirm that the predictability question we address is a live and unresolved one specifically for shipping equities, rather than a generic asset-pricing exercise.

We assume that the investor can decide among two investment strategies, one is to hold stock and the other is to invest in Treasury bill therefore and in practice the investor can pursue three strategies, the first one is to hold the stock, the second is to hold the Treasury bill and the third is to switch between these two. For switching between stock and Treasury bill we assume 20% transaction cost which will be deducted from the associated period t return. This transaction cost is constant at 20% of the return for all the transactions. The decision for switching gets back to the result of the one step ahead forecast return for each of the model selection criterion. The investor cannot compare the results of the different model selection criterion at every step and it's assumed that choice of the selection criterion is constant throughout the whole period of investment. We will compare the results of pursing any of the statistical criterion, AIC and BIC. In order for the investor to reach a decision, he buys or keep the stock if the forecast of the excess return is bigger than zero $\hat{r}_{t+1} \geq 0$ and he invest in Treasury bill if $\hat{r}_{t+1} \leq 0$.

1.2. The Data

We apply our model to the prices of the NYSE:FRO In order to study the macroeconomic determinants of the Maritime Company's stock market. Frontline Ltd (OSE:FRO, NYSE:FRO) is one of the world largest oil tanker Maritime Company's companies based in Bermuda and is controlled by Norway's richest man John Fredriksen. The company has a fleet of 82 tankers in total consisting of VLCC, Suezmax and Suezmax OBO carriers. We consider 8 explanatory variables that are potentially relevant for forecasting Maritime Company's stock returns. They all have been taken from Thomson Financial Datastream. We use mid of the month data. The list of explanatory variables contains 8 variables. The Treasury bill is a 4 week for the switching matter but in the regressors section we use the return of a 3 month Treasury bill. We account for the fact that macroeconomic data are published with time lag. Therefore we apply the two months lagged industrial production series and purchasing indexes but the rest of the regressors are accounted with one lag.

Table1. NYSE: FRO Variables Description.

Frontline Variebles Description			
Name	Description	Start	Finish
Y	Frontline (NYS)	15/09/1994	15/05/2010
TB	US Treasury Bill 2ND MKT 4-WK – Middle Rate		
	Forcasting Period	15/07/2001	15/03/2010

Frontline Stock Regressors Effective: 104- start: 85		Full length: 188-
X1	S&P GSCI Commodity Spot - PRICE INDEX	No of lags : 1
X2	Moody's Commodities Index - PRICE INDEX	1
X3	Crude Oil WTI NYMEX Spot U$/BBL	1
X4	MLCX Spot Index - Price Index	1
X5	US ISM Purchasing Man. Index (MFG Survey) SADJ	2
X6	US Industrial Production VOLA	2
X7	US PPI - Finished Goods SADJ	2
X8	US Treasury Bill 2ND Market 3 Month - Middle Rate	1

The 8 variables are all the change in the natural logarithms. We have not included any dummy variable. Initially the US unemployment rate, Baltic Exchange Tanker index, Brent crude oil and a few exchange rates had been included in the regressors set but they had zero inclusion rates and therefore they were substituted. This does not mean that the results have been engineered but we will discuss this and the possibility of data snooping further in the coming sections.

2. Results

We report in table 5 the performace of the competing strategies for the FRO stock including the comparison with S&P 500 performance during the same period. The buy and hold R_{BH} generates a summation of 140% during the whole period and 4 weeks Trasury bill generates 17%, this is compared to the net return of the switching strategy which is less than R_{BH} in all the permutation cases however the gross return is bigger than R_{BH}. The difference between gross R_{GR} and net R_{NE} is that a transation cost of 20% of the return had been deducted for every time an investor has switched between the stock and Trasury bill. The sequence of the best selection models is 1. FRO: All Variable 2. FRO: BIC 3. FRO: AIC 4. FRO: R-square.

Table2. Sum of Return Series.

Frontline	R_{NE}	R_{GR}	R_{BH}	R_{TB}
FRO: AIC	0.97	1.59	1.40	
FRO: R-square	0.77	1.49		
FRO: BIC	1.07	1.64		

FRO: All Variables	2.06	2.72		0.17
S&P: AIC	0.10	0.33	0.03	
S&P: R-square	0.03	0.23		
S&P: BIC	0.36	0.19		
S&P: All Variables	0.49	0.66		

2.1.Transaction Costs and Strategy Viability

A striking feature of the results above is the magnitude of the gap between the gross and net return of every switching strategy: for the FRO all-variable model, for example, the cumulative gross return of 2.72 falls to 2.06 once the 20% round-trip transaction cost is deducted, and the ranking of strategies changes once costs are introduced. This is not a statistical artefact but a substantive result for the shipping industry. Because tanker companies operate with thin, cyclical margins and high fixed operating costs, the profitability of any active trading rule built on their equity is unusually sensitive to the frictions of implementation — bid-ask spreads, market impact and the cost of frequently reallocating capital. The practical implication is that a forecasting model's statistical accuracy is a necessary but not sufficient condition for it to be useful to an investor or corporate treasury: a model that appears to "win" on gross returns can lose its advantage, or even underperform a passive buy-and-hold position, once realistic transaction costs are applied. This reinforces the case, made throughout this section, for evaluating forecasting models on a net-of-cost basis whenever the intended audience includes practitioners.

In the case of S&P 500 the results are different, R_{BH} generates lower profit than all switching cases or Treasury bill. The sequence of the best models is similar to the FRO. Considering the fact that the inevstor is not aware of the best selection model to use in the case of FRO, buy and hold is a more convenient option and in the case of S&P 500, the Treasury bill generates a better return .The PT (1995) approch does not yield any benefit according to these criterias.The frequency of the return series could be different which means the equal summation of two equal series may produce a complete different returns when we simulate a specific investemnt. Therefore we consider an intial investment of $100 and calculate the countinuous comound for final investment.

Table3. Final Investment.

Frontline 100 USD	W_{NE} \$	W_{GR} \$	W_{BH} \$	W_{TB} \$
FRO: AIC	264.24	492.29	408.37	119.37
FRO: R-square	216.94	444.93		
FRO: BIC	291.80	518.07		
FRO: All Variables	791.40	1520.89		
S&P: AIC	111.41	139.48	103.94	
S&P: R-square	103.43	126.00		
S&P: BIC	121.47	144.26		
S&P: All Variables	163.54	193.83		

The table 5 suggest that for $100 investment for the period 15/07/2001- 15/03/2010 pursuing the switching will generate an least income of $216.94, comparatively this is less than buy and hold which is W_{BH} = $408.37 .It worth looking at the relevant graphs which gives a better idea to compare the different strategies.

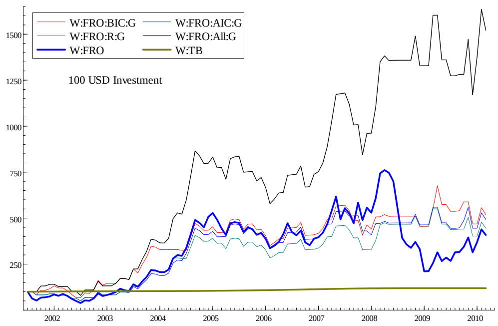

Figure1. Graph of FRO Growth Investment 15/07/2001-15/03/2010.

The above graph illustraes the ups and down of the $100 invetment when there is no transaction cost. It's clear that the inclusion of all variables has performed better than the other alternatives and all of the models have passed the buy and hold crash of 2008 succesfully and smothly. The resason that the all variables model is performing better lies in the fact that we have a strong set of regressors. In the case that the choosen regressors were not strong enough then the permutaton models may have performed better. The other reason could be that the model selection criterions are not efficient enough.

This pattern is consistent with the structural characteristics of the shipping industry. Freight income, and therefore tanker-company earnings, is driven by a derived demand that reacts to global trade, industrial output and commodity prices simultaneously, and is subject to abrupt regime shifts around business-cycle turning points and geopolitical shocks (Grammenos & Arkoulis, 2002; Kamal et al., 2021). A model restricted to a single selection criterion effectively bets on one narrow channel of transmission remaining dominant throughout the sample; when the industry's exposure to shocks causes the dominant driver to change from one structural break to the next — for instance from oil prices to industrial production, or from commodity indices to freight-market sentiment — a narrow model is systematically wrong-footed at exactly the points where returns are largest. The all-variable specification, by contrast, retains every channel simultaneously and is therefore mechanically robust to which factor happens to be driving returns in a given sub-period. In an industry as internationally exposed and cyclically volatile as tanker shipping, this robustness advantage plausibly outweighs the efficiency loss from including weaker regressors, which is why the broad-spectrum model dominates the narrower permutation and information-criterion-based models in our results.

The results of the inevstment strategy and the difference between permutation models and all models seems to be unusual. The problem lie in the way the model selection criterion works, it appears that the model selections does not work well. This is perhaps because of the fact that the stock series are non stationary and there are strctural breaks in the data so the regression results and consequently the model selection criterion results will not be correct.

Let's assume that in a regression period we have X1 and X2 is picked up by e.g. AIC but if there is a structural break and the correct significant variables are X1 and X3 then in the all model forcast all the X1, X2, X3 are included and hence the results are better. So the permutauin model is under performing because our data contain some structural breaks. We can overcome this by finding the breaks and applying the appropriate beta in the regression but this could be a potential extension to this chapter and we do not investigate it here. The similar graph considering the transaction cost is very different to the previous one.

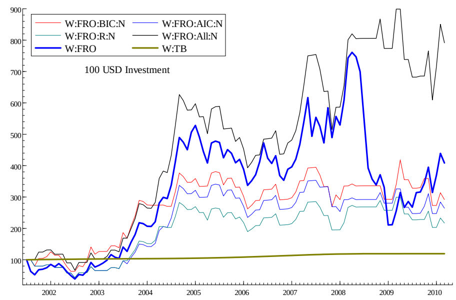

Figure2. Graph of FRO Net Investment 15/07/2001-15/03/2010.

The thick blue line is the buy and hold graph which is performing better than the permutaion models however they did not crashed in the 2009 buy and hold crash. All variable model is performing better than the others in most years. This graph confirms that the permuation models are not a smart techniques. The Treasury bill is worst investment except and until the mid 2003, the comaprion of the wealth creasion of Trasury bill and the worst performing permutaion model is below:

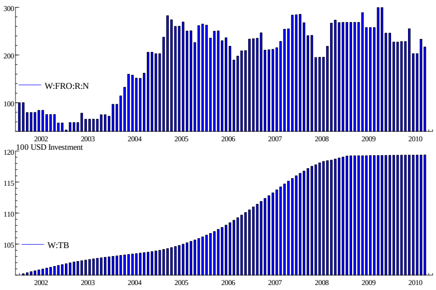

Figure3. Comparison of Treasury bill and the worst performing model.

It's quite clear from all the graphs that the Trasury bill is not a feasible investment at alThe "Crude Oil WTI NYMEX" and "MLCX Spot Index " has the highest level of inclusion. The "US Industrial Production" and "US PPI - Finished Goods" has the lowest level of inclusion. The below graph compares the FRO with the two most strongest regressors.

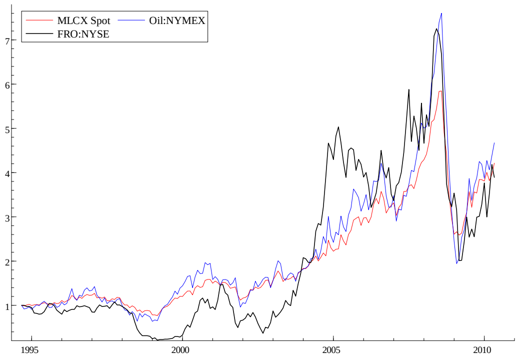

Figure4. Graph of Prices.

It should be noticed that the frequency of the inclusion is not normaly distributed during the time. It's intersting to consider how many variables are participating in every period. The coming graphs are the comaprion of different frequencies. Only X2 fills the early parts of the charts although the X3 and X4 and the most included but the perhaps the X2 (Modeey's commodity index) is the most important variables.

Now we compare the investment simulation of S&P similar to FRO to check it there is any similarity between the findings.

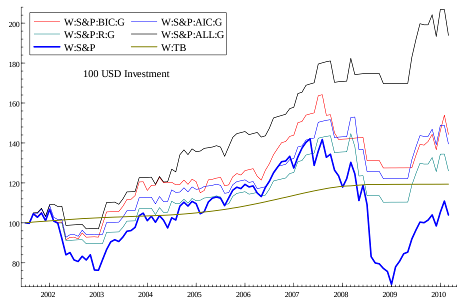

Figure5. Graph of S&P Growth Investment 15/07/2001-15/03/2010.

The investment path for the S&P 500 differs markedly from that of FRO. The buy-and-hold line for the index underperforms the Treasury bill in almost half of the sample and only overtakes it during the 2005-2009 boom, whereas for FRO the buy-and-hold strategy is consistently competitive. This is best understood as a consequence of the different nature of the two instruments: FRO is a single-industry, single-company equity whose returns are driven by a small set of concentrated, cyclical factors — tanker freight rates, oil demand and vessel supply — while the S&P 500 is a broadly diversified index whose returns average out idiosyncratic sector shocks. Because a single shipping stock carries more concentrated, factor-specific risk than a diversified index, it is more exposed to the extreme upswings and downswings of the shipping cycle documented elsewhere in this paper (Grammenos & Arkoulis, 2002), but for the same reason a forecasting model that correctly identifies the relevant macro-commodity drivers has more exploitable signal to work with in the FRO case than in the S&P 500 case. The all variables model is still outperforming the rest of the models for both instruments, and the switching models are not performing very well once the 20% transaction cost is inserted into the model, with the permutation models performing no better than the Treasury bill.

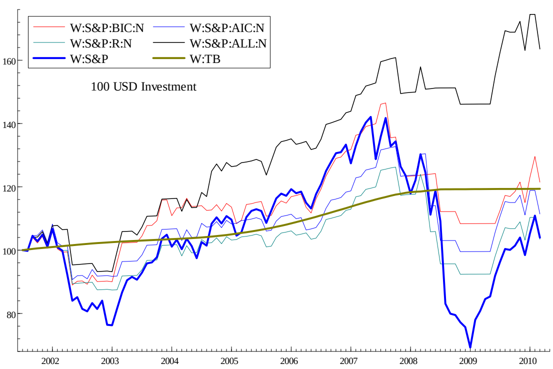

Figure6. Graph of S&P investment 15/07/2001- 15/03/2010.

During the crises in 2003 the TB has the best performance. Between 2004 to early 2008 which is a boom time the buy and hold pefroms relatively well but then carshes in 2008, the permutation models realised the correct signs at the middle of the crash with BIC at the top but during this time the general performance of the permutation models are negative compare to the TB. To have the better understanding of the statistical difference between our alternatives we report the result of the statistical description for Trasury bill, FRO:N and FRO:G which are the net and gross Frontline return series. Here we check if the mean of the switchung series are any different Treasury bill. We choose the best performed model of *FRO:All: Net*, and an average performed model of *FRO:AIC:Net* and we compare them with Treasury bill. We perform the ttest and the results are below. For the average performed AIC in the second row the mean is not any different from Trasury bill but for the other one, the means are statistically different from each other, therefore we can conclude that base on the fact that the investor may choose any selection criterion then the switching return series are not any different from Treasury bill.

Table4. t-test of the selected switching return series and Treasury bill.

pp test =0	TestStat	CriticalValue	pvalue	Hypotheis
TB-Fro:aic:net	-0.6043	-0.0196 0.0104	0.5463	Failure to reject
TB:Fro:all:net	4.2488	0.0004 0.0010	0.00002	reject

Now we examine the effect of any single variable, we noticed that all variables model is performing better that the permutation variables. It's unclear at this stage what the investor would have faced if any single variables would have been considered innstead os a series of variables. We test for those of varibles indidvidually to find out the indivual performances.

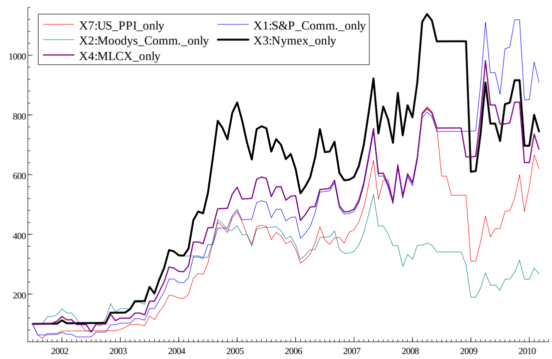

Figure7. FRO Effect of Individual Variables.

If the PT (1995) strategy relies only on Nymex oil price, the inevstment will be on top of the other alternatives at most of the times. Using S&P Commodity Index however will yeild a better final sum. In general Nymex oil is a better regressor except from the 2009 credit crunch. This process is not the similar in the next graphs, the Treasury bill is the most powerful regressors in both FRO and S&P 500. Individual regressors seem to be working better than any other combinations even between permutaion or all variable model.

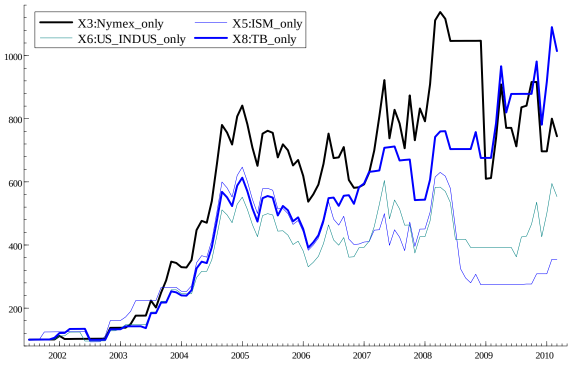

Figure8. FRO Effect of Individual Variables(X1: S&P GSCI Commodity Spot - X2: Moody's Commodities Index- X4: MLCX Spot Index - X5: US ISM Purchasing Man- X6: US Industrial Production- X7: US PPI - Finished Goods).

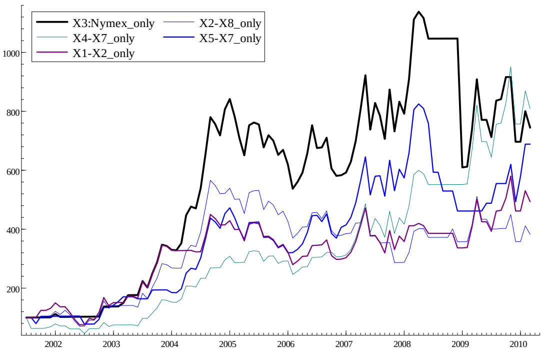

Figure9. FRO Effect of Individual Variables

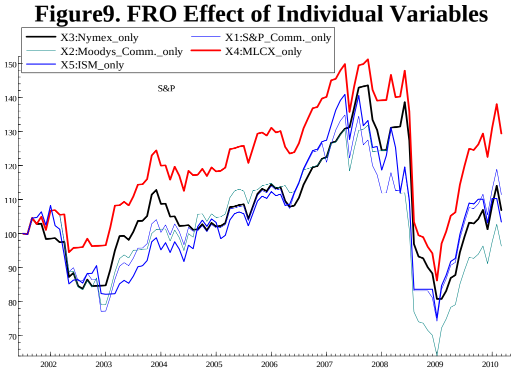

Figure10. S&P 500 Effect of Individual Variables.(X1: S&P GSCI Commodity Spot - X2: Moody's Commodities Index - X4: MLCX Spot Index - X5: US ISM Purchasing Man- X6: US Industrial Production- X7: US PPI - Finished Goods).

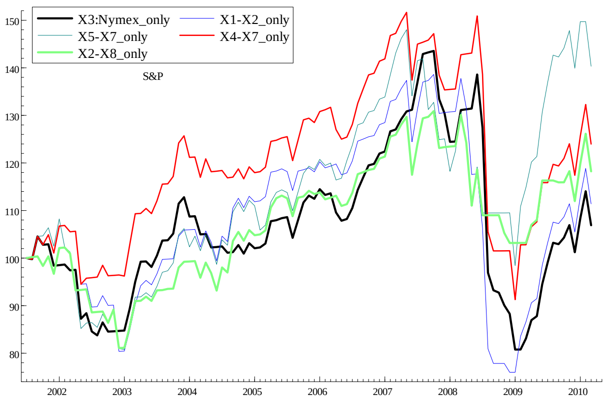

Figure11.S&P 500 Effect of Individual Variables.

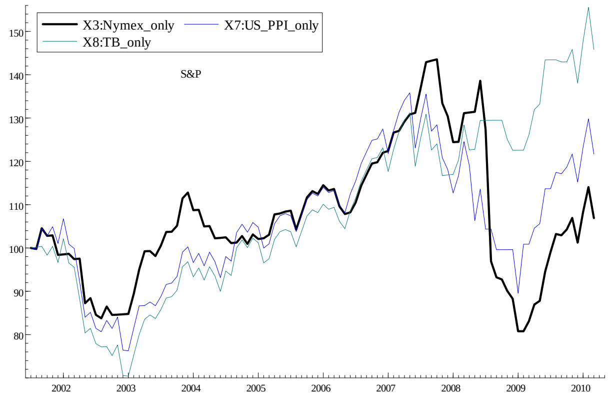

Figure12. S&P 500 Effect of Individual Variables.

In FRO stock, forecasting with Treasury Bill yields almost four times bigger final investment sum than trading with FRO R-square. The permeation models are the worst performing ones and the All Variable model stands in between. When we get to the S&P 500, the results is not quite the same but similar to FRO. In S&P 500 forecasting with Treasury Bill still yield a higher sum but the All Variable model is the best performing model. Permutation models are not very attractive choices, the comparison of all alternatives is in Table 8.

Table5. Final Investment all alternatives.

Frontline 100 USD	W_{NE} $	W_{BH} $	W_{TB} $
FRO: X8:TB_only	1014.46	408.37	119.37
FRO: X1:S&P_Comm._only	909.24		
FRO: X3:Nymex_only	744.57		
FRO: X4:MLCX_only	684.66		
FRO: X7:US_PPI_only	619.65		
FRO: X6:US_INDUS_only	553.31		
FRO: X5:ISM_only	354.64		
FRO: X2:Moodys_Comm._only	266.86		
FRO:X4-X7_only	808.89		
FRO:X5-X7_only	688.63		
FRO:X1-X2_only	493.45		
FRO:X2-X8_only	382.49		
FRO: AIC	*264.24*		
FRO: R-square	*216.94*		
FRO: BIC	*291.80*		
FRO: All Variables	*791.40*		
S&P: X8:TB_only	145.80	103.94	
S&P: X1:S&P_Comm._only	111.46		
S&P: X3:Nymex_only	106.89		
S&P: X4:MLCX_only	129.36		
S&P: X7:US_PPI_only	121.65		
S&P: X6:US_INDUS_only	141.85		
S&P: X5:ISM_only	103.39		

S&P: X2:Moodys_Comm._only	96.29		
S&P:X4-X7_only	123.98		
S&P:X5-X7_only	140.32		
S&P:X1-X2_only	111.39		
S&P:X2-X8_only	118.23		
S&P: AIC	*111.41*		
S&P: R-square	*103.43*		
S&P: BIC	*121.47*		
S&P: All Variables	*163.54*		

We noticed from the previous sections that the results of Frontline and S&P are completely of a different nature and hence and we compare the results of the three more Maritime Company's companies, these companies similar to the Frontline and specilast tanker Maritime Company's companies.

Table6. Knightsbridge Tankers Variables.

VLCCF Variebles Description			
Name	Description	Start	Finish
Y	NASDAQ: VLCCF	15/05/2000	15/05/2010
TB	US Treasury Bill 2ND MKT 4-WK – Middle Rate		
	Forcasting Period	15/01/2006	15/05/2010
VLCCF Stock Regressors 120- Effective 52- start 68th			Full length
X1	KNIGHTSBRIDGE TKRS. - DIVIDEND YIELD	no lags:	1
X2	S&P GSCI Commodity Spot - PRICE INDEX		ˋ
X3	Moody's Commodities Index - PRICE INDEX		ˋ
X4	Crude Oil, WTI NYMEX Spot U$/BBL		ˋ
X5	US INDUSTRIAL PRODUCTION VOLA		2
X6	US PPI - FINISHED GOODS SADJ		2
X7	BD IND. PRO. INCLUDING CONS.(%YOY) VOLA (Germany)		2
X8	CH INDUSTRIAL PRODUCTION INDEX VOLN		2

The regressors are partly different from the previous set of regressors used.

Table7. VLCCF Sum of Returns.

VLCCF	R_{NE}	R_{GR}	R_{BH}	R_{TB}
VLCCF: AIC	-0.10	0.12	-0.32	0.09
VLCCF: R-square	0.44	0.64		
VLCCF: BIC	0.13	0.36		
VLCCF: All Variables	0.54	0.76		

The sum of net return is negative for AIC and the buy and hold also produces a negative sum of return. In the three out of four models the switching produces a much bigger return than Treasury bill.

Table8.VLCCF Final Investment.

VLCCF 100 USD	W_{NE} $	W_{GR} $	W_{BH} $	W_{TB} $
VLCCF: AIC	90	113.8	72.2	110.4
VLCCF: R-square	155.9	189.7		
VLCCF: BIC	111.5	143.5		
VLCCF: All Variables	172.7	215.7		

The buy and hold produces the worst results and the all variable model is the best alternative.The dividend yield has a high rate of inclusion in addition to the China industrial production and US PPI, however there is no strong pattern of inclusion of dis inclusion in the above Table.

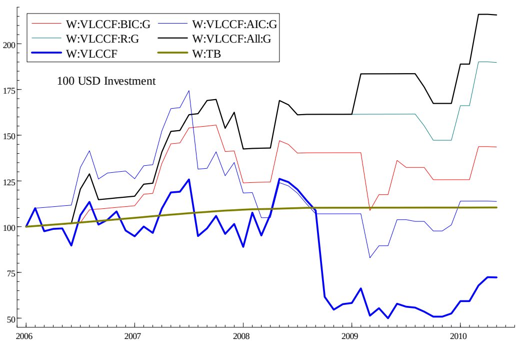

Figure13. Graph of VLCCF Gross investment 15/01/2006-15/05/2010.

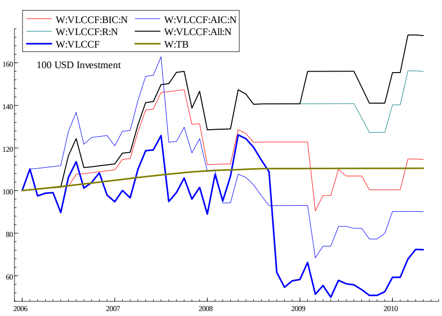

Figure14. Graph of VLCCF Net investment 15/01/2006-15/05/2010.

Both of the above graphs indicate the underperformance of the buy and hold strategy, the all variable model and the R-selection criterion are performing better than the others. In the FRO stock the R-square was the worst performing selection criterion. The treasury bill which is the thick red line have a relatively average performance much better than the VLCCF:AIC. The All models and R-square has a similar performance until 2009.

Table9.“NASDAQ: NAT” Variables Descriptions.

Nordic American Tanker Ship			
Name	Description	Start	Finish
Y	NASDAQ: NAT	15/11/1997	15/05/2010
TB	US Treasury Bill 2ND MKT 4-WK – Middle Rate	15/11/1997	
Forcasting Period		15/04/2003	15/05/2010
NAT Stock Regressors – Effective: 86 - start: 65		Full length: 150	
X1	LME-LMEX Index - Price Index	No of lags: 1	
X2	S&P GSCI Commodity Spot - Price Index	1	
X3	Crude Oil, WTI NYMEX Spot U$/BBL	1	
X4	Crude Oil-Brent Cur. Month FOB U$/BBL	1	
X5	MLCX Spot Index - PRICE INDEX	1	
X6	CBOE SPX Volatility VIX (New) - Price Index	1	
X7	US Industrial Production VOLA	2	
X8	US Treasury bill 3 MONTH – Middle Rate	1	

In addition to the usual set of variables it contains two types of oil prices, NYMEX and Brent Crude oil, it also contain VIX and Treasury bill.

Table10. NAT Sum of Return Series.

NAT	R_{NE}	R_{GR}	R_{BH}	R_{TB}
NAT: AIC	0.45	0.64	0.78	0.15
NAT: R-square	0.33	0.59		
NAT: BIC	0.12	0.45		
NAT: All Variables	1.68	1.95		

The summation of variables in most cases, except BIC net return is bigger than R_{TB} however R_{BH} which is the buy and hold, produces an impressive %78 which is bigger than all the permutation models.

Table11. VLCCF Final Investment.

NAT	W_{NE} \$	W_{GR} \$	W_{BH} \$	W_{TB} \$
NAT: AIC	158.2	191.3	219.5	116.3
NAT: R-square	139.3	182.2		
NAT: BIC	112.9	157.6		
NAT: All Variables	538.4	704.9		

The final figure of the investment is in inline with the summation of returns. The All Variables model produces almost 2.5 times of return compare to buy and hold but the rest of permutation models are not performing well.

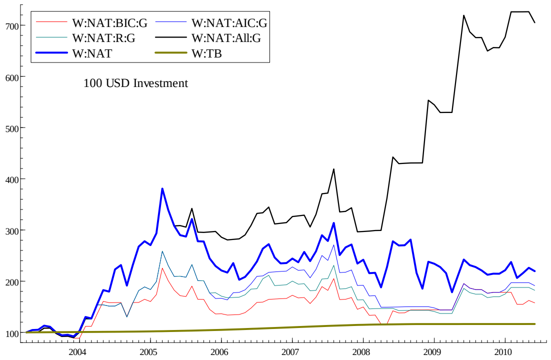

Figure15. Graph of NAT Gross investment 15/04/2003-15/05/2010.

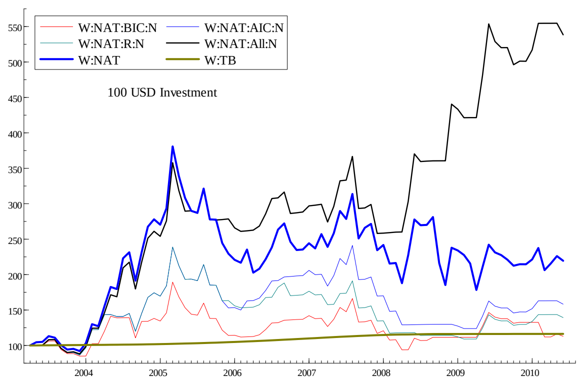

Figure16.Graph of NAT Net Investment 15/04/2003-15/05/2010.

Table12. "NYSE:TK" Description of Variables.

Teekay Corpotration			
Name	Description	Start	Finish
Y	NYSE:TK	15/10/1995	15/04/2010
TB	US Treasury Bill 2ND MKT 4-WK – Middle Rate		
Forcasting Period		15/12/2001	15/04/2010
Stock Regressors		Full length 175 – Effective 101- start 74	
X1	Teekay – Dividend YIELD	No of lags:	1
X2	Crude Oil, WTI NYMEX Spot U$/BBL		1
X3	US CPI – All Urban: All Items SADJ		2
X4	Crude Oil-Iranian Light FOB U$/BBL		1
X5	US Consumer Confidence Index SADJ		2
X6	US Industrial Production VOLA		2
X7	CH Industrial Production Index VOLN		2
X8	BD Ind. Pro. Inc. const. (%YOY) VOLA		2

The base of regressors include two sets of oil prices and three sets of industrial production indexes for United States, Germany and China.

Table13. TK Sum of Return Series.

TK	R_{NE}	R_{GR}	R_{BH}	R_{TB}
TK: AIC	0.16	0.61	0.67	0.17
TK: R-square	0.91	1.15		
TK: BIC	0.20	0.68		
TK: All Variables	2.08	2.47		

The R-square has the best performance between the permutation models. The summation of the All Variable model is significantly better than the other models. Although the sumation of the AIC net is slightly less than TB but the return of the final investment is $117.5 compre to the TB which is $108.

Table14. TK Final Investment.

TK	W_{NE} $	W_{GR} $	W_{BH} $	W_{TB} $
TK: AIC	117.5	172.1	148.2	108
TK: R-square	250.1	294.2		
TK: BIC	122.8	183.2		
TK: All Variables	746.8	1103.8		

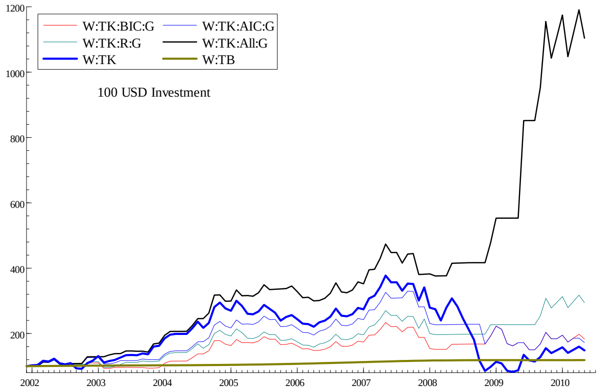

Figure17. Graph of TK Gross Investment 15/12/2001-15/05/2010.

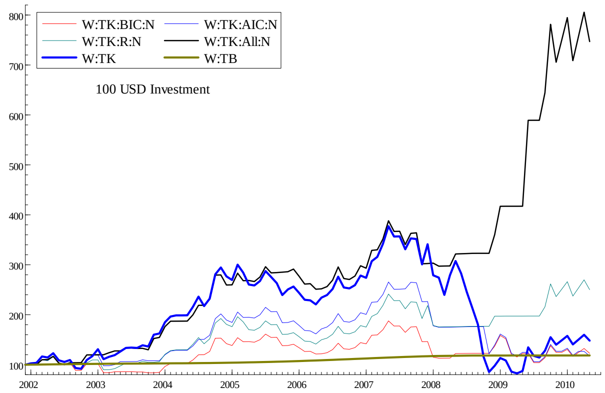

Figure18. Graph of TK Net Investment 15/12/2001-15/05/2010.

The All varible model almost follows the buy and hold strategy until the market crash at the middle of the 2008 starts. TB does not have any feasible performance except at the times of the depression.

2.2. Remarks

The all variable model performs better that the other variables however if the regressors are being replaced with weak, irrelevent variables then the permutation models will perform better. Between the model selection criterion there is no specific pattern or winning model. Between the base set of regressors, the NYMEX and the US Industrisal Productions are the frequently included variabls. Between all the AIC may show a more number of included variables. The findings reflect results from Welch and Goyal 2008 which suggest how difficult it is to forecast out of sample forecast. [13,16] and [14] claim that the performance of forecasting the return is limited to recession periods [10-11],[17], [14] and [15] all have challenged the validity of the assumption of constant regression coeffieicnts in the linear system return regression.

Table15. Winners

Stock	Investment winning models	Most included variables
FRO	All- BIC-AIC-R…TB	MLCX, NYMEX
S&P	All- BIC-AIC-R…TB	IS INDUS, NYMEX
VLCCF	All-R-BIC...TB...AIC	DY, US PPI, China INDUS (All %100)
NAT	All-AIC-R…TB…BIC	S&P Comm, TB
TK	All-R-BIC-AIC…TB	NYMEX, US CPI, Oil light, US Conf, China INDUS, GER INDUS (All %100)

2.3.Considerations for Maritime Domain Specialists

The results carry three practical implications for specialists working in the maritime domain. First, the outperformance of the all-variable model over narrower, criterion-selected models suggests that risk managers and treasury functions at Maritime Company's companies should be cautious about relying on a single macro-financial indicator (e.g., oil prices alone) when assessing market risk, since the dominant driver of equity returns shifts across the cycle. Second, the wide gap between gross and net returns documented above implies that any active hedging or trading strategy built around such forecasts must be evaluated net of realistic transaction costs before being considered for operational use. Third, the comparison between FRO and the S&P 500 illustrates that single-industry shipping equities behave quite differently from a diversified market index, which is relevant to fleet owners and lenders using equity-market signals as a proxy for sector-wide investment conditions: such signals should be read as company- and segment-specific rather than as a simple mirror of the broad market.

3. Conclusion

In recent years the credit crunch and the business cycle in the water transport market has yield a new insight into how the empirical modeling research. Very little reasrch has studies the implications of the macroecomomic factors on Maritime Company's companies stock. We have used macroeconomics and financial database to analyse the predictibility of the Maritime Company's stock return. The results are not inline with the previous literature. We found that the return predictility in permutation models was not as good as fixed simple models. Our set of that contains one or two periods of a serious stock market crashand hence the results of the investmnet strategy was mixed however ths results can be very different if we divide the dataset into, before and after the market carsh, but this would be the manipulation data of and can not reflect an investor's simulation of the events. Consistent with findings in previous studies the results improve further if economically motivated restrictions or multivariate informations are imposed, similar studies include [18] and [19].

A further limitation is that, although the empirical model is estimated on data from actual Maritime Company's companies (Frontline, Knightsbridge Tankers, Nordic American Tankers and Teekay Corporation), it relies exclusively on economy-wide macroeconomic and commodity variables and does not incorporate the micro-level operational variables that are specific to shipping companies, such as daily spot and time-charter rates, bunker (fuel) prices, vessel utilisation, or the orderbook-to-fleet ratio. These variables are known to affect shipping-company earnings and valuation directly (Wang et al., 2014; Mohanty et al., 2021) and were not included here because they were not available at consistent monthly frequency over the full sample period for all five companies studied. This is a genuine constraint on the model rather than a design choice, and it points to a concrete opportunity for future research: integrating macro-financial forecasting models of the kind developed here with operational shipping-market data could materially improve both the accuracy and the industrial interpretability of stock-return forecasts for maritime companies.

For the maritime engineering audience, these findings reinforce the view that shipping-company equity behaves as a leading proxy for the sector's investment cycle: periods in which broad, multi-factor models outperform narrow ones coincide with periods of heightened capital-market uncertainty about the industry, information that is complementary to physical-market signals such as the orderbook-to-fleet ratio or newbuilding prices.

Building on these findings, we identify three feasible directions for future research. First, the operational-data extension discussed above — incorporating time-charter rates, bunker fuel prices and fleet-utilisation data alongside the macroeconomic regressors used here — could be implemented directly within the same recursive framework, since these series are increasingly available at monthly frequency from shipping-market data providers. Second, the structural breaks identified informally above could be modelled explicitly using regime-switching or time-varying-parameter extensions of the recursive approach (e.g., following Dangl & Halling, 2012), which would formally test whether accounting for breaks recovers the performance advantage of the narrower, information-criterion-based models relative to the all-variable model. Third, the five-company sample used here could be extended to a panel of Maritime Company's companies across dry bulk, container and gas-carrier segments, allowing the segment-specific sensitivity of return predictability to macroeconomic and commodity shocks to be tested formally rather than descriptively.

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