Understanding the Influencers of Freight Rate Forecasting Accuracy: A Meta-Regression Analysis of the Literature

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Abstract

Forecasting freight rates has been a topic of discussion for decades. Even though freight rate forecasting is regarded as a critical research topic in shipping, the literature lacks a systematic empirical account of how to obtain more reliable and accurate freight rate forecasts. This study uses meta-regression to synthesize the literature on freight rate forecasting and to test various accuracy influencers. The study confirms that the accuracy of the freight rate forecasts depends significantly on data frequency, forecasting horizon and method, market type, sample size, and the inclusion of explanatory variables.

Keywords: Meta-Analysis, Freight rate, Forecasting, Accuracy, Shipping

1. Introduction

Shipping indices, such as Baltic Dry Index (BDI), play a crucial role in making various decisions in the shipping industry [1,2]. However, it is usually arduous to accurately assess and forecast the freight markets since BDI fluctuates with a large amplitude [1,3]. For instance, BDI rose to 11793 in May 2008, fell 95% in the next six months, and reached 663 points [4]. Zhang et al. [2] explained that volatility of BDI is high because of a series of dynamic random factors; hence irregular and non-stationary features of freight rates limit the impact of forecasting models in practice. Similarly, freight rates in container and tanker markets suffer from high volatility.

Since critical decision-making is complex and vital in such an unpredictable industry, forecasting may help to facilitate decision-making. Any additional information about the future direction of the market volatility has paramount importance due to the magnitude of shipping investments [5]. This volatile nature of the shipping freight rates has attracted much attention by researchers in terms of analysing quantitatively [6] and resulted in applying complex techniques [7]. However, Duru et al. [3] highlighted the difficulties in obtaining reliable and accurate forecasts of freight rates in shipping markets. This importance of accurate freight rate forecasts has led to extensive attempts to enhance the accuracy of forecasting methods [6]. Previous researches generally indicates that no single forecasting method outperforms in all conditions [2]. Therefore, the following questions are still posed: "Is there any pattern to get more reliable and accurate freight rate forecasts" and "which influencers affect freight rate forecasting?" Although there is a consensus on the influencing factors, opinions contradict how these factors affect forecasting accuracy. This study attempts to narrow this reach gap by exploring these influencing factors' effects on freight rate forecasting accuracy. In line with this aim, this study follows a Meta-Regression methodology to provide a comprehensive and systematic review of prior freight rate forecasting studies. Most of the previous literature reviews were based on qualitative analysis and lacked quantitative proof [8]. Therefore, Meta-Regression is preferred since it provides quantitative proof.

We organized this paper as follows: Section 2 contains the proposed hypotheses based on the literature on freight rate forecasting models. Section 3 describes the materials and

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methods, including identification, coding, and methodology, while Section 4 provides detailed empirical results and an evaluation of forecasting accuracy. This study ends with a conclusion emphasizing the work's relevance of the work for practice and future research.

2. Proposed Hypotheses

Although the studies on freight forecasting have gained momentum recently, the results are objectionable since it is difficult to comprehend freight series' non-linear and non-stationary features [9]. Scholars offered various factors that could explain the surfeit of performance variability among several forecasting models such as the forecasting horizon, data availability, level of aggregation, type of product, and historical stability of data series [10]. However, it is not clear which attributes might affect the forecasting accuracy. Therefore, it is essential to examine the most suitable composite patterns for such forecasts in the industry. Therefore, we propose a series of hypotheses in this section to study characteristics of forecasting accuracy.

Traditional non-causal and causal econometric models such as ARIMA, VAR, VECM, GARCH are the most widely used models in freight rate forecasting e.g. [11-13]. On the other side, scholars suggested soft computing methods for non-linear functions in the recent two decades. Artificial neural networks (ANN) are the most explored e.g. [7,14]. Additional soft computing models such as support vector machine (SVM), wavelet neural networks (WNN) are also used. There is also a tendency to compare the proposed methods with the conventional econometric models. For instance, it is claimed that the SVM model has ascendancy in both the trend and the forecast precision [15]. Furthermore, ANN e.g. [16] and WNN models e.g. [5] also deliver notable results compared with the conventional benchmark mode. However, it is not possible to generalize that soft computing models always give better results, and it still has some deficiencies, such as parameter sensitivity and the possibility of overfitting [17]. Munim and Schramm [6] reported that simple models are better than complicated models. For instance, while Santos et al. [16] found that the performance of ANN modeling outperforms ARIMA, Munim and Schramm [18] claimed that not only ARIMA models but also VAR/VEC outperform ANN models. Geomelos and Xideas [19] reported that it is possible to reduce the forecasting errors by combining models. In this context, various hybrid models such as ANN-based combinations e.g. [20], fuzzy integrated methods e.g. [21], and ensemble forecasting models [17] have been developed. It is indicated that the proposed models are superior compared to the conventional benchmarks. On the other side, Zeng and Qu [22] forecasted BDI using econometric, soft computing,

and hybrid models and found close accuracy rates. To sum up, although each proposed model offers strong evidence, claiming better accuracy than the others, accuracy varies according to the structure of the models used. Therefore, since there is no consensus on the issue, we developed the following hypothesis to reveal the effect of the forecasting method on forecasting accuracy.

H_1: The modeling method employed significantly affects the accuracy of freight rate forecasting.

Shipping markets based on the transported cargo have quite different dynamics. Although the majority of the literature consists of studies on the dry bulk shipping market e.g. [4, 23] due to market maturity and data availability, there is increasing attention on freight forecasting in the container market e.g. [6,18,24] and tanker market e.g. [16,25,26]. Zeng et al. [9] asserted that more empirical studies for freight rates of different ship types would provide contributions to confirm the reliability and applicability of the methods proposed. We extend this suggestion over the container, tanker, and dry bulk shipping markets, and given each market has unique characteristics. Hence, we put forward the following hypothesis:

H_2: Type of the market significantly affects the accuracy of freight rate forecasting.

It generally tends to form forecasting models with exogenous variables for complex dynamic processes [7,16,18,20]. However, there are findings that forecasting attempts using auxiliary information show higher accuracy e.g. [1, 7]. According to this common explanation, the positive effects are observed between explanatory variables and freight rate forecasting accuracy. However, positive effects are by no means guaranteed to increase the accuracy. Also, theoretically, exceptions might have occurred. Thus, we have an intention to determine whether explanatory variables have a positive impact on forecasting accuracy with the following hypothesis:

H_3: Explanatory variables have a positive effect on the accuracy of freight rate forecasting.

The shipping industry suffers from volatility, cyclicality, seasonality, and noise [1,27]. This structure of the shipping industry affects forecasting accuracy. Extending this rationale, Randers and Göluke [27] indicated that there is only noise in shorter time horizons and the accuracy of the forecast is lower in longer time horizons due to unpredictable events' impact on cyclicality. Although it is impossible to make point forecasts, a high likelihood of success in forecasting accuracy could be achieved. In this sense, Munim and Schramm [6] emphasized that it is necessary to forecast freight rates over different forecasting horizons to confirm the models' robustness. Some scholars

found that short-term forecasts can obtain accurate forecasts [7]. For instance, Nielsen et al. [24] asserted that the developed forecasting model should be at least six weeks out of sample with a MAPE value of less than 5 percent. It is a consensus that the long-term validity of the models is weak and time-lag effects for short-term forecasting have attracted scholars e.g. [6,20]. Kasimati and Veraros [28] claimed that shorter time horizons with smaller ships improve the quality of the forecasts. However, Cullinane et al. [11] stated that extremely long-term horizons could obtain accurate forecasts due to the asset investment in the physical shipping markets. As a result, there are different and conflicting perspectives in some cases on the forecasting horizon. Given the inconsistencies in the literature, we qualify this hypothesis by asking whether the accuracy of the freight rate forecasts is affected by the forecasting horizon.

H_4: Forecasting horizon affects the accuracy of freight rate forecasting.

Sample size should be designed to describe data variation tendencies. As proposed by Nielsen et al. [24], it is crucial to balance the forecast horizon and the sample size used to fit the model for the desired accuracy. Similarly, Gharehgozli et al. [21] highlighted that utilizing the entire sample to improve the forecasting accuracy of freight rates would not be a rule of thumb. Duru et al. [3] emphasized that a shorter sample period is important for achieving or improving accuracy. To sum up, the sample size in forecasting models appears to be controversial. Therefore, we propose the following hypothesis to reveal the impact of sample size on the accuracy of the freight rate forecasts:

H_5: Sample size affects the accuracy of freight rate forecasting.

Data frequency is another factor that influences the predictive power of the models. Results suggest that different data frequencies give different results, especially depending on the models used. Zhang et al. [2] found that DFN-AI models exhibited more significance in the weekly BDI predictions than daily data forecasting. Munim and Schramm [6] found that the ARIMARCH model outperforms ARIMA models while performing short-term weekly predictions. Empirical findings suggest that data frequency influences the accuracy of the freight rates, but results also vary regarding the modeling methods used. In this context, the influence of data frequency on freight rate forecasting should be investigated in detail since the picture seems fuzzy. Furthermore, it should be clarified whether there is any influence of data frequency apart from the used modeling method. Thus, to properly understand these nuances, we proposed the following hypothesis:

H_6: Data frequency affects the accuracy of freight rate forecasting.

3. Materials and Methods

3.1. Identification, Screening, and Classification of Studies

We a systematic search strategy to identify all relevant studies. First, various databases were used to identify both peer-reviewed and grey literature. Then, as "search in" options, we select "Article Title, Abstract, Keywords," "Topic," "Title, Keywords, Abstract," "Item Title, Abstract," "Title, Abstract," and "Title, Keywords." The optimal keywords after iterative keyword screening were "freight forecast*" and "freight rate forecast*."

Timespan was set as "all years" for each inquiry, so all relevant papers up to September 17, 2020, were listed in the identification phase. Although no language was selected in the search terms, we progressed only to studies published in English. This process yielded 1878 results, of which 1242 results are from Scopus, 541 are from Web of Science, 34 are from Wiley Online Library, 27 are from Jstor, 19 are from Emerald, and 15 are from Taylor and Francis Online. Here 475 duplicates were removed and the search yielded 1403 novel references as depicted in Figure 1 based on the protocol of Moher et al. [29]. In the screening phase, we reviewed each of the remaining studies separately within the scope of research and found 1166 studies as irrelevant. Studies that are not related with shipping and forecasting were regarded as irrelevant. The remaining 237 studies were evaluated within the scope of eligibility, and it was determined that 182 of them were not related to freight rate forecasting accuracy. In addition, we could not access nine studies, and 46 studies remaining. Additionally, we added 14 studies from the references of those studies, and we reached 60 studies on freight rate forecasting accuracy. However, since various accuracy metrics were used in these studies, we selected RMSE and MAPE among those that employed different accuracy metrics. Finally, we included 24 studies that used RMSE and 17 studies that used MAPE for accuracy metrics in the meta-analysis. Details of all studies used for conducting meta-analysis are available upon request.

3.2. Coding

The influencing variables were grouped and coded based on the selection criteria mentioned above. The authors initially coded each article to improve coding accuracy. We started with a coding strategy including country, source title, aim, findings, accuracy measurement, market type, modelling method, data source, explanatory variable, forecasting horizon, and sample size. The data was then checked for coding errors. If there were disagreements about the codes,
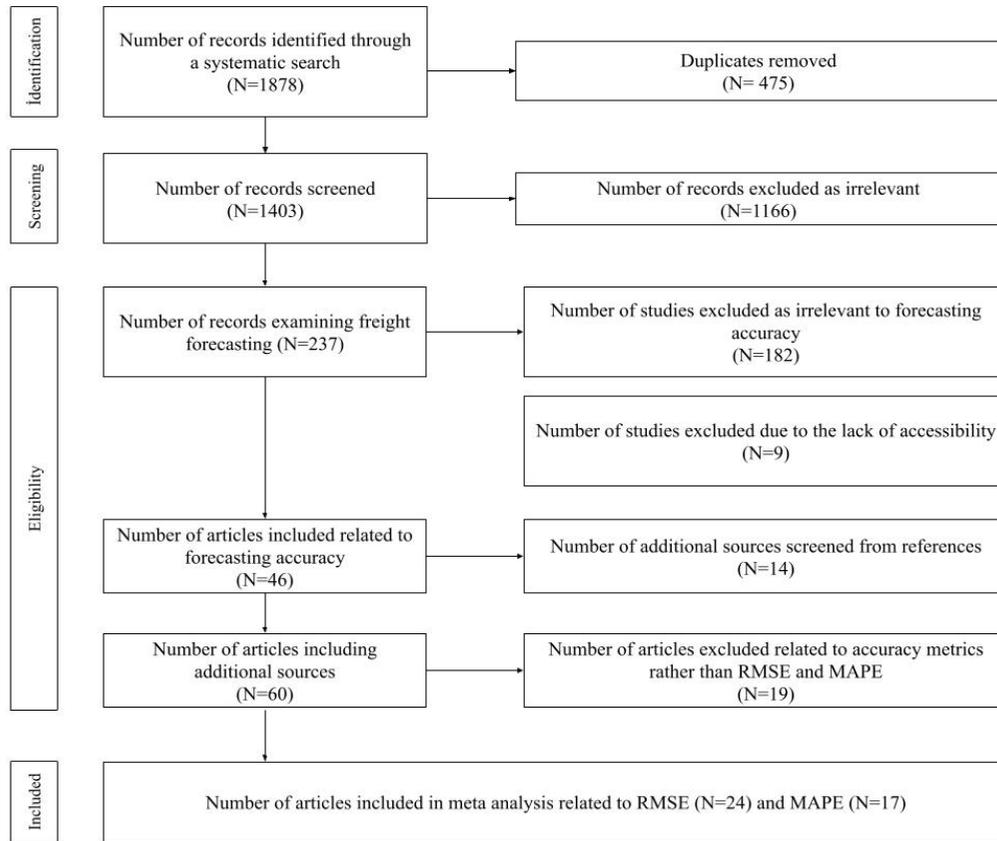
Figure 1. *A flowchart of the screening protocol and the publications that were included*

the articles were advanced screened until a consensus was reached. Table 1 provided a definition of coded data as well as basic descriptive statistics. By utilizing these variables, this study intends to evaluate the hypotheses above.

Detailed data to articles in the Meta-Regression with respective descriptive statistics for RMSE and MAPE would be provided upon request. Finally, 878 RMSE observations from 24 studies were used, as were 276 MAPE observations from 17 studies. In these studies, forecasting accuracy measures such as RMSE (40.0%), MAPE (28.4%), and Theil's U (11.6%) were most commonly used. Only MAPE and RMSE are included in the Meta-Regression due to comparability.

3.3. Meta-Regression Methodology

In this study, a Meta-Regression methodology is applied to explain the effects of different modeling variations on the accuracy of freight rate forecasting studies. The effect size used in the study is the forecasting errors collected from the papers used for meta-analysis, as in Sebri [30]. As indicated by Nelson and Kennedy [31], model-specific challenges arise as heteroscedasticity, heterogeneity, and non-independence of observations, as well as non-normality problems, while estimating Meta-Regression models. To overcome these

problems and ensure the robustness of the empirical results, three estimators are employed in this study: Ordinary least squares (OLS), weighted least squares (WLS), and quantile regression (QR). First, to achieve the objective of this study, generic Meta-Regression is estimated with OLS in Equation 1 and 2:

$$\text{Log(MAPE)}_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon \qquad (1)$$

$$\text{Log(RMSE)}_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon \qquad (2)$$

where MAPE_i and RMSE_i are the estimates taken from the ith study, β_0 reflects true effect/intercept, β_k is the coefficients of independent variables, X_k is the meta-independent variables taken from the ith study, and ε is the error term. OLS estimation of Eq. 1 is biased due to heteroscedasticity as indicated by the results of the Breusch-Pagan heteroscedasticity test shown in Table 2. Then to reduce heteroscedasticity for more efficient estimation, known as the WLS, is estimated. In WLS, weights are taken as the inverse logarithm of the sample size. QR, a robust alternative to these regression methods, is also utilized in this paper

due to its robustness against heteroscedasticity and normal distribution assumption. We selected five representative quantile points (10th, 25th, 50th, 75th, and 90th). There is no empirical consensus on which quantile to use and mostly, a selection of the quantile made arbitrarily [32]. The optimal quantile was selected using box plots shown in Figure 2. In some quantiles, the differences between OLS, WLS models, and QR models were small. In contrast, especially in RMSE models, there were differences to a great extent in the distributions of the fitted values. QR model in 50th quantile for both RMSE and MAPE estimates presented similar estimates to those of the OLS model. Therefore, the estimated QR model in the 50th quantile was selected as the empirical model to be referenced result.

Table 1. *Variable definition and descriptive statistics*

| Variable	Description	Codes from MAPE estimations			Codes from RMSE estimations		
		No	Mean	Std. Dev.	No	Mean	Std. Dev.
Dependent Variable							
MAPE	The MAPE's reported value	276	1.5358	7.1940	-	-	-
RMSE	The RMSE's reported value	-	-	-	878	433.580	3060.041
Independent Variables							
Forecast Periodicity							
Daily	A dummy variable equal to 1 if the data used are of daily frequency, 0 otherwise.	103	0.3786	0.4859	132	0.1505	0.3577
Weekly	A dummy variable equal to 1 if the data used are of weekly frequency, 0 otherwise.	105	0.3860	0.4877	93	0.1060	0.3080
Monthly[a]	A dummy variable equal to 1 if the data used are of monthly frequency, 0 otherwise.	59	0.2169	0.4129	643	0.7331	0.4425
Yearly	A dummy variable equal to 1 if the data used are of annual frequency, 0 otherwise.	5	0.0183	0.1345	9	0.0102	0.1008
Forecasting Horizon							
Short-run	A dummy variable equal to 1 if the study deals with short-run forecasts, 0 otherwise.	209	0.7683	0.4226	504	0.5746	0.4946
Medium-run[a]	A dummy variable equal to 1 if the study deals with medium-run forecasts, 0 otherwise.	56	0.2058	0.4050	227	0.2588	0.4382
Long-run	A dummy variable equal to 1 if the study deals with long-run forecasts, 0 otherwise.	7	0.0257	0.1586	146	0.1664	0.3727
Forecasting Method							
Econometric	A dummy variable equal to 1 if an econometric model was employed, 0 otherwise.	73	0.2683	0.4439	689	0.7856	0.4106
Soft Computing	A dummy variable equal to 1 if a soft computing model was employed, 0 otherwise.	101	0.3713	0.4840	95	0.1083	0.3109
Hybrid[a]	A dummy variable equal to 1 if a hybrid model was employed, 0 otherwise.	98	0.3602	0.4809	93	0.1060	0.3080
Type of the Market							
Dry market	A dummy variable equal to 1 if dry market was targeted, 0 otherwise.	214	0.7867	0.4103	564	0.6431	0.4793
Tanker[a]	A dummy variable equal to 1 if tanker market was targeted, 0 otherwise.	14	0.0514	0.2213	285	0.3249	0.4686
Container	A dummy variable equal to 1 if container market was targeted, 0 otherwise.	44	0.1617	0.3689	28	0.0319	0.1759
Other Characteristics							
Sample size	The study sample size	272	776.0259	1220.532	878	401.961	576.534
Explanatory variables	A dummy variable equal to 1 if an explanatory variable was used, 0 otherwise.	32	0.1176	0.3227	345	0.3933	0.4887
[a]Indicates an omitted category in the meta-regression estimation							
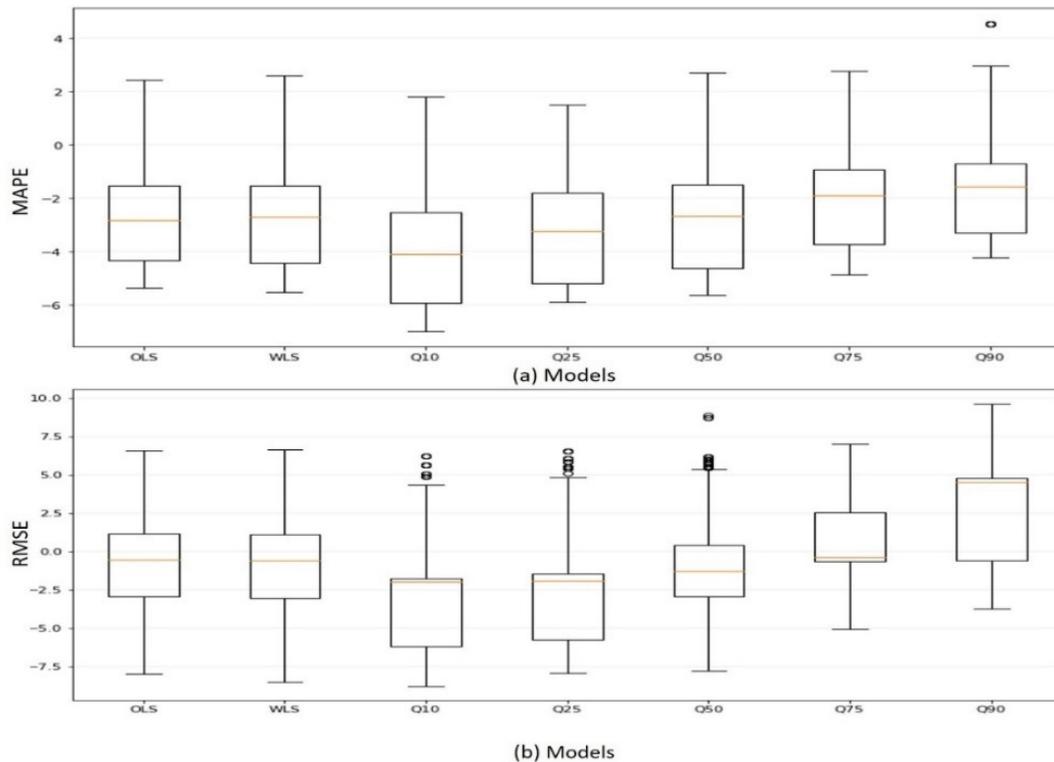
Figure 2. Boxplot of the estimated models for MAPE (a) and RMSE (b)

4. Results and Discussion

Table 2 summarizes the Meta-Regression and test results for the hypothesis (H1-H6). The adjusted R^2 values show that the Meta-Regression models are successful in explaining 59.6% of the variation in log (RMSE) and 69.7% in log (MAPE). The pseudo-R^2 is also used to evaluate the QR models' goodness of fit. Since the number of studies using RMSE (24 studies, 878 observations) is significantly greater than the number of studies reporting MAPE (17 studies, 276 observations), log(MAPE) Meta-Regression results should be regarded as additional analysis and a sensitivity check for log (RMSE) estimates. The regression results show that, the forecasting accuracies of the different forecasting metrics vary in some models (while soft computing methods have a significant effect on MAPE estimates, they present an insignificant effect in RMSE estimates). The reasons can be considered as the amount of studies employed for the analysis and the information loss caused by the accuracy metrics as similarly indicated by Liu et al. [10]. Extending this rationale, it is explained as RMSE is based on the scale of the data, while MAPE is based on percentage errors. Therefore, the magnitude of the effect in the RMSE models is greater than in the MAPE models, which is consistent with the supporting arguments for the differences discussed above.

As illustrated in Table 2, hypotheses H_1 is supported. Log (RMSE) estimates suggest that econometric models have a negative and highly significant coefficient, while soft computing models have insignificant coefficients; that is, econometric models tend to provide more accurate forecasts. Log (MAPE) estimates present positive and highly significant coefficients for both modeling methods. This means that the forecasting accuracies of the different models change significantly, and when the two methods were compared, econometric models outperformed the soft computing methods. The outcome of this estimation supports similar findings by Munim and Schramm [18]. For H_2, the forecasting accuracies of the different markets differ significantly. Both log (RMSE) and log (MAPE) present highly significant results (except for the container market in RMSE with OLS regression). Our expectation in this regard is consistently supported due to the relatively short history of the tanker, and container freight rate forecasting studies. However, BDI dates back to 1985, and many scholars have attempted to forecast BDI and explore enhancing the forecasting accuracy of BDI. This finding confirms Zeng et al. [9] as more empirical studies are needed for freight rate forecasts, including various market types and their sub-indexes. It is hypothesized in H_3 that including an explanatory variable would positively influence the accuracy of the forecasting freight rates. As expected, it decreases forecasting error in the log (RMSE) estimates and agrees with the findings of Lyridis et al. [25] and Yang and Mehmed [7]. However, log (MAPE) estimates

Table 2. Meta-regression estimates for freight forecasting accuracy

Model	RMSE							MAPE						
Variable	OLS	WLS	Quantile 10th quant	Quantile 25th quant	Quantile 50th quant	Quantile 75th quant	Quantile 90th quant	OLS	WLS	Quantile 10th quant	Quantile 25th quant	Quantile 50th quant	Quantile 75th quant	Quantile 90th quant
Intercept	5.1103***	5.2544***	4.8191***	4.3663	3.0152***	3.9429***	6.7039***	1.3082***	1.7347*	-0.8683	0.7074	1.6125***	1.9069	1.7346***
	(0.904)	(0.911)	(0.425)	(0.494)	(0.360)	(0.711)	(0.498)	(0.726)	(0.724)	(0.738)	(0.515)	(0.664)	(0.747)	(1.050)
Forecast Periodicity														
Daily	-0.969**	-0.9111***	0.8737***	0.3563***	-1.4276***	0.7326**	2.2784***	-3.0080***	-3.0106***	-4.3887***	-3.1664***	-2.7285***	-2.2313	-2.6545***
	(0.4137)	(0.413)	(0.177)	(0.215)	(0.165)	(0.366)	(0.298)	(0.287)	(0.274)	(0.330)	(0.221)	(0.262)	(0.244)	(0.250)
Weekly	-0.574	-0.7985*	2.3973***	1.9616***	-0.0995	-0.2503	-1.4951***	-1.3579***	-1.2813***	-2.1545***	-1.3654***	-0.9881***	-0.7328	-0.4840**
	(0.363)	(0.343)	(0.158)	(0.180)	(0.145)	(0.310)	(0.245)	(0.234)	(0.214)	(0.230)	(0.166)	(0.214)	(0.205)	(0.219)
Yearly	3.5011***	3.4690***	3.0223***	2.9663***	5.9387***	4.9953***	5.4549***	3.6610***	3.5361***	1.2757	1.6652*	5.4682***	5.5117	6.0595***
	(0.866)	(0.887)	(0.370)	(0.488)	(0.345)	(0.631)	(0.768)	(0.9618)	(0.918)	(1.750)	(0.888)	(0.878)	(1.016)	(1.585)
Forecasting Horizon														
Short-run	2.3288***	2.5886***	-0.5669***	-0.4431***	1.8474***	3.5174***	6.5900***	-0.2314	-0.1601	-0.1003	-0.1901	-0.3273*	-0.1448	0.0405
	(0.252)	(0.259)	(0.106)	(0.131)	(0.101)	(0.213)	(0.203)	(0.196)	(0.196)	(0.185)	(0.135)	(0.180)	(0.182)	(0.213)
Long-run	0.6337*	0.6814**	-0.1583	-0.0896	-0.0619	0.3654*	-0.0451	-1.4729	-1.2351	-1.2840	-1.5110*	-1.4430*	-1.6954	-2.5837*
	(0.281)	(0.291)	(0.123)	(0.151)	(0.112)	(0.207)	(0.181)	(0.908)	(0.860)	(1.727)	(0.863)	(0.830)	(0.951)	(1.551)
Forecasting Method														
Econometric	-2.5154***	-2.3407***	-2.0184***	-3.1719***	-4.0988***	-2.1509***	0.0233	0.2137	0.1953	-0.7073**	0.0862	0.4733***	0.7821	1.0948***
	(0.354)	(0.345)	(0.168)	(0.189)	(0.141)	(0.309)	(0.305)	(0.193)	(0.192)	(0.227)	(0.152)	(0.177)	(0.159)	(0.161)
Soft Computing	0.4488	0.3556	0.5747***	0.6838***	0.1630	0.1937	0.6977**	0.7595***	0.7727***	0.3859***	0.3818***	0.5690***	0.7149	0.8849***
	(0.367)	(0.354)	(0.159)	(0.189)	(0.146)	(0.283)	(0.238)	(0.169)	(0.164)	(0.178)	(0.132)	(0.155)	(0.138)	(0.145)
Type of the Market														
Dry market	2.4293***	2.7718***	4.3894***	3.9442***	3.3189***	2.5365***	1.5864***	-2.0837***	-2.3866***	-1.1470*	-1.575***	-2.1359***	-2.4023	-3.2756***
	(0.254)	(0.267)	(0.082)	(0.113)	(0.101)	(0.243)	(0.207)	(0.464)	(0.468)	(0.422)	(0.312)	(0.424)	(0.500)	(0.724)
Container	-0.0646	0.3556	-1.8540***	-2.0694***	-0.7474***	-0.0216	0.9220**	-1.5257***	-1.7208***	-0.8238*	-1.2889***	-1.7198***	-1.9493	-3.4061***
	(0.596)	(0.571)	(0.239)	(0.294)	(0.237)	(0.501)	(0.415)	(0.451)	(0.454)	(0.449)	(0.321)	(0.412)	(0.434)	(0.575)
Other Characteristics														
Sample size[a]	-0.994***	-1.1050***	-1.6207***	-1.2118***	-0.6285***	-0.8971***	-1.6102***	-0.1627*	-0.2029*	0.0342	-0.2002***	-0.2442***	-0.2379	-0.0060
	(0.155)	(0.153)	(0.080)	(0.103)	(0.062)	(0.137)	(0.116)	(0.080)	(0.081)	(0.096)	(0.063)	(0.073)	(0.070)	(0.078)
Explanatory variables	-2.8542***	-2.9819***	-0.2179***	-0.3792***	-0.5333***	-1.2762***	-0.6624***	1.4776***	1.3371***	2.2041***	1.6726***	1.3470***	1.4833	1.9350***
	(0.232)	(0.237)	(0.076)	(0.103)	(0.092)	(0.230)	(0.183)	(0.329)	(0.319)	(0.321)	(0.221)	(0.301)	(0.347)	(0.501)
Estimation Summary Statistics														
F-Statistic (p-value)	118.7*** (0.0000)	138*** (0.0000)	-	-	-	-	-	58.7*** (0.000)	59.94*** (0.000)	-	-	-	-	-
Breush-Pagan test (p-value)	135.63*** (0.000)	-	-	-	-	-	-	44.46*** (0.000)	-	-	-	-	-	-
AdjR²	0.5964	0.6324	-	-	-	-	-	0.6977	0.702	-	-	-	-	-
Pseudo R²	-	-	0.4789	0.42338	0.4147	0.4664	0.4689	-	-	0.4948	0.5276	0.5251	0.5232	0.5453
Number of Observations	878	878	878	878	878	878	878	276	276	276	276	276	276	276

***, ** and * indicate statistical significance at the 99%, 95% and 90% confidence levels, respectively. Standard errors are presented in parentheses below coefficient estimates.
[a]Log transformation of sample values

yielded contradictory results. This may be attributed to the information loss mentioned above. However, a closer examination of this difference is needed to identify the reasons for the negative impact in MAPE estimation. For forecasting horizon (H_4), Log (RMSE) estimations reveal positive and significant coefficients in short-run forecasts at 99% confidence level (OLS, WLS, and QR 50th models), but not in long-run forecasts at 90% confidence level (OLS, WLS, and QR 50th models) in forecasting horizon (H_4) (OLS and WLS models). There is no significant difference in forecasting accuracy between the OLS and WLS estimates of log (MAPE). The QR 50th model, on the other hand, has negative and statistically significant coefficients in both horizons at a 90% confidence level.

The log (RMSE) and log (MAPE) findings imply that short-run forecasts provide less accurate forecasts than long-term ones. However, this finding contradicts the theoretical expectations and assumption of previous findings wherein the accuracy of the forecasting models tends to decline with a longer forecasting horizon e.g. [30]. This implies the short-term horizon of the freight rate yields less accurate forecasts than the long-term horizon. This unexpected result stems from the nature of the freight forecasting studies attributed to the number of studies and the models used. The studies on freight rates have mainly focused on medium to long-term forecast horizons [24]. Similarly, the usage of dynamic models could be the other reason for this result, as dynamic econometric models provide better forecasts for longer horizons [33]. The results of the H_5 prove with a negative and highly correlated coefficient that the sample size influences the forecasting accuracy. This finding is consistent with the popular argument that larger sample sizes should reduce the accuracy of freight rate forecasting, as suggested by Sebri [30]. However, it should be noted that there are conflicting findings in previous studies wherein large sample sizes did not necessarily increase accuracy rate, and in some instances, yielded worse results.

The results support the hypothesis (H_6), where the forecasting accuracy of freight rate forecasts depends on data frequency. Daily and weekly data have negative signed coefficients, while annual data have positive coefficients. However, previous literature in the forecasting practice of other industries stating that forecasting with annual data presents more accurate forecasts [30]. It is reported that lower frequency data (yearly, quarterly, and monthly) tend to produce higher forecasting accuracies due to the complex seasonal characteristics of the high-frequency data (weekly, daily, and hourly). Freight rate forecasting studies generally consist of daily, weekly, monthly, and yearly data. Even though shipping markets are subject to recurrent heavy seasonality, we found that the forecasting accuracy of freight

rate forecasting increased when the higher frequency data was employed. However, this unexpected result stems from the nature of the freight forecasting studies. Daily and weekly forecasts are required more frequently than quarterly or yearly ones in this context. The studies on freight rates have mainly focused on high-frequency data and these forecasts are used for supporting short-term strategic decisions.

5. Conclusion and Implications for Future Research

In this study, we aimed at revealing the patterns of obtaining accurate freight rate forecasts by identifying quantitative explanations using Meta-Regression methodology. Recently, Duru et al. [3] reported the need to identify the influencers of freight rate forecasting to achieve accurate and reliable forecasts. However, no previous statistical and quantitative review has been carried out to the best of our knowledge on this issue. This motivates us to conduct a Meta-Regression to contribute to the growing literature of freight rate forecasting by providing robust and novel empirical evidence revealing the determinants of forecast accuracy. The results confirm that data frequency, forecasting horizon and method, market type, sample size, and inclusion of the explanatory variables significantly affect the accuracy of the freight rate forecasts. The research also summarizes the state-of-the-art freight rate forecasting literature and builds future research directions for this important topic.

We conducted a detailed analysis of the literature using quantitative approaches, considering the extensive research on freight rate forecasting. For the first time, a comprehensive data set is collected, including 878 observations for RMSE and 276 observations for MAPE, and Meta-Regression is used to determine the influencing variables. The main contribution of the study is twofold: first, it compares quantile regression, a robust alternative, to OLS and WLS. The results of this study are more robust because it presented many estimates and used more than one accuracy metric. Second, this study adds to previous reviews by providing quantitative evidence.

As far as the policy implications of this study are concerned, this study argues that the shipping industry is highly volatile and unpredictable due to the dependence on exogenous factors such as complexity, cycles, extreme times, and developments of the world economy, and irrational decisions of the market players. Therefore, there is no chance of success for point forecasting in the industry. When forecasting freight rates, we suggest policymakers, forecasters, and other market players consider employing daily data, explanatory variables, data for submarkets and different routes, small sample size, and long-term horizon while developing their forecasting models. It should be

noted that these results should be considered as auxiliary and that such models are case-specific and subject to change. Each attempt based on hyperparameter optimization or daily performance dynamic combination forecasts are also used to govern such method shifts. Ideally, their use is recommended in conjunction with empirical knowledge. Even if forecasting practices' experiments include various methods and different hyperparameters during the model development, this study could suggest a starting point. Moreover, it was detected that qualitative forecasts had been encountered in freight rate forecasting literature infrequently. We also suggest that a tendency to focus on qualitative studies might increase the accuracy of the freight rate forecasts. This supports the implications of Munim and Schramm [18]. Although Schramm and Munim [34] recently attempted to integrate judgements into the forecasting practice, more research is required in this domain.

Our research is expected to be of value to industry practitioners and scholars as it reveals a deeper understanding on the effects of influencing variables on the freight rate forecasting model and thus helps to clarify the model development stage. Although researchers and practitioners in the shipping industry tend to agree that freight rate forecasting is important, there are contrasting views on how different models with various specifications are considered in different circumstances. We provide a synthesis of the growing, but diverged, literature on freight rate forecasting through this Meta-Regression analysis. The results inform about important influencers of the accurate freight rate forecasting models and their effects. These results can serve as a basis for future freight rate forecasting studies as for developing their models.

This study, like all others, has some limitations. A constraint could be publication bias, which evaluates only published articles. As a result, the future inclusion of unpublished studies may improve the reliability of Meta-Regression analysis. Due to sample limitations, it should be necessary to re-evaluate the influencers' impacts in the future as the number of relevant studies increases over time. Furthermore, we divided the forecasting techniques into three categories for the purpose of this study, but; however, future studies may include additional approach subclassification if the sample size grows significantly. Despite the large number of studies and observations examined in this study, only the MAPE and RMSE metrics were examined. Future research is encouraged to publish additional forecasting measures that can be used to benchmark findings. Another limitation is that we did not consider the number of explanatory variables, the lag, or the country of publication of the freight rate forecasting research. In the future, studies may investigate this issue as well.

Authorship Contributions

References

[1]   C. C. Chou, and K. S. Lin, "A fuzzy neural network combined with technical indicators and its application to Baltic Dry Index forecasting," *Journal of Marine Engineering & Technology*, vol. 18, pp. 82-91, Jul 2019.

[2]   X. Zhang, M. Y. Chen, M. G. Wang, Y. E. Ge, and H. E. Stanley, "A novel hybrid approach to Baltic Dry Index forecasting based on a combined dynamic fluctuation network and artificial intelligence method," *Applied Mathematics and Computation*, vol. 361, pp. 499–516, Nov 2019.

[3]   O. Duru, E. Gulay, and K. Bekiroglu, "Predictability of the Physical Shipping Market by Freight Derivatives," *IEEE Transactions on Engineering Management*, pp. 1-13, Jan 2021.

[4]   C-C. Chang, H. C. Chou, and C. C. Wu. "Value-at-Risk Analysis of the Asymmetric Long-Memory Volatility Process of Dry Bulk Freight Rates." Maritime Economics & Logistics, vol. 16, pp. 298–320, June 2014.

[5]   Y. Leonov, and V. Nikolov, "A wavelet and neural network model for the prediction of dry bulk shipping indices," *Maritime Economics & Logistics*, vol. 14, pp. 319–333, Aug 2012.

[6]   Z. H. Munim, and H. J. Schramm, "Forecasting container shipping freight rates for the Far East – Northern Europe trade lane," *Maritime Economics & Logistics*, vol. 19, pp. 106-125, Oct 2017.

[7]   Z. Yang, and E. E. Mehmed, "Artificial neural networks in freight rate forecasting," *Maritime Economics & Logistics*, vol. 21, pp. 390-414, Apr 2019.

[8]   W. Shi, and K. X. Li, "Themes and tools of maritime transport research during 2000-2014," *Maritime Policy & Management*, vol. 44, pp. 151-169, 2017.

[9]   Q. Zeng, C. Qu, A. K. Y. Ng, and X. Zhao, "A new approach for Baltic Dry Index forecasting based on empirical mode decomposition and neural networks," *Maritime Economics & Logistics*, vol. 18, pp. 192-210, 2016.

[10]   A. Liu, V. S. Lin, G. Li, and H. Song., "Ex Ante Tourism Forecasting Assessment." *Journal of Travel Research*. vol. 61, pp.64-75, Jan 2022.

[11]   K. Cullinane, K. J. Mason, and M. Cape, "A Comparison of Models for Forecasting the Baltic Freight Index: Box-Jenkins Revisited," *International Journal of Maritime Economics*, vol. 1, pp. 15-39, Oct 1999.

[12]   C. M. I. C. Taib, and Z. I. Mohtar, "Forecasting Spot Freight Rates using Vector Error Correction Model in the Dry Bulk Market," *Malaysian Journal of Mathematical Sciences*, vol. 12, pp. 235-253, Mar 2018.

[13]   M. G. Kavussanos, and N. K. Nomikos, "Price Discovery, Causality and Forecasting in the Freight Futures Market," *Review of Derivatives Research*, vol. 6, pp. 203-230, Oct 2003.

[14] B. Şahin, S. Gürgen, B. Ünver, and İ. Altın, "Forecasting the Baltic Dry Index by using an artificial neural network approach," *Turkish Journal of Electrical Engineering and Computer Science*, vol. 26, pp. 1673-1684, Jun 2018.

[15] Q. Han, B. Yan, G. Ning, and B. Yu, "Forecasting Dry Bulk Freight Index with Improved SVM," *Mathematical Problems in Engineering*, vol. 2014, pp. 1-12, Jun 2014.

[16] A. A. P. Santos, L. N. Junkes, and F. C. M. Pires Jr, "Forecasting period charter rates of VLCC tankers through neural networks: A comparison of alternative approaches," *Maritime Economics & Logistics*, vol. 16, pp. 72-91, 2014.

[17] J. Li, J. Hao, Q. Q. Feng, X. Sun, and M. Liu, "Optimal selection of heterogeneous ensemble strategies of time series forecasting with multi-objective programming," *Expert Systems with Applications*, vol. 166, pp. 114091, Mar 2021.

[18] Z. H. Munim, and H. J. Schramm, "Forecasting container freight rates for major trade routes: a comparison of artificial neural networks and conventional models," *Maritime Economics & Logistics*, vol. 23, pp. 310-327, Apr 2020.

[19] N. D. Geomelos, and E. Xideas, "Forecasting spot prices in bulk shipping using multivariate and univariate models," *Cogent Economics & Finance*, vol. 2, pp. 923701, Jul 2014.

[20] P. Eslami, K. Jung, D. Lee, and A. Tjolleng, "Predicting tanker freight rates using parsimonious variables and a hybrid artificial neural network with an adaptive genetic algorithm," *Maritime Economics & Logistics,* vol. 19, pp. 538-550, Aug 2017.

[21] A. Gharehgozli, O. Duru, and E. Bulut, "Input data range optimization for freight rate forecasting using the rolling window testing procedure," *International Journal of Transport Economics*, vol. 45, pp. 393-413, 2018.

[22] Q. Zeng, and C. Qu, "An approach for Baltic Dry Index analysis based on empirical mode decomposition," *Maritime Policy & Management*, vol. 41, pp. 224-240, 2014.

[23] S. Chen, H. Meersman, and E. de van Voorde, "Forecasting spot rates at main routes in the dry bulk market," *Maritime Economics & Logistics*, vol. 14, pp. 498-537, Oct 2012.

[24] P. Nielsen, L. Jiang, N. G. M. Rytter, and G. Chen, "An investigation of forecast horizon and observation fit's influence on an econometric rate forecast model in the liner shipping industry," *Maritime Policy & Management*, vol. 41, pp. 667-682, Nov 2014.

[25] D. V. Lyridis, P. Zacharioudakis, P. Mitrou, and A. Mylonas, "Forecasting Tanker Market Using Artificial Neural Networks," *Maritime Economics & Logistics*, vol. 6, pp. 93-108, Jun 2004.

[26] C. von Spreckelsen, H. J. von Mettenheim, and M. H. Breitner, "Short-Term Trading Performance of Spot Freight Rates and Derivatives in the Tanker Shipping Market: Do Neural Networks Provide Suitable Results?," C. Jayne, S. Yue, and L. Iliadis, Eds. International Conference on Engineering Applications of Neural Networks, Springer, Berlin, Heidelberg, EANN 2012, CCIS 311, 2012, pp. 443-452.

[27] J. Randers, and U. Göluke, "Forecasting turning points in shipping freight rates: lessons from 30 years of practical effort," *System Dynamics Review*, vol. 23, pp. 253-284, Oct 2007.

[28] E. Kasimati, and N. Veraros, "Accuracy of forward freight agreements in forecasting future freight rates," *Applied Economics*, vol. 50, pp. 743-756, 2018.

[29] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and PRISMA Group, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," Annals of Internal Medicine, vol. 151, pp. 264-269, Jul 2009.

[30] M. Sebri, "Forecasting urban water demand: A meta-regression analysis," *Journal of Environmental Management,* vol. 183, pp. 777-785, Dec 2016.

[31] J. P. Nelson, and P. E. Kennedy, "The Use (and Abuse) of Meta-Analysis in Environmental and Natural Resource Economics: An Assessment," *Environmental and Resource Economics*, vol. 42, pp. 345-377, 2009.

[32] S. Jradi, C. F. Parmeter, and J. Ruggiero, "Quantile estimation of the stochastic frontier model," *Economics Letters*, vol. 182, pp. 15-18, Sep 2019.

[33] B.Peng, S. Haiyan, and C.I. Geoffrey, "A Meta-Analysis of İnternational Tourism Demand Forecasting and Implications for Practice," *Tourism Management*, vol. 45, pp. 181–93, Dec 2014.

[34] H. J. Schramm, and Z. H. Munim, "Container freight rate forecasting with improved accuracy by integrating soft facts from practitioners," *Research in Transportation Business & Management,* vol. 41, pp. 100662, Dec 2021.