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Research Article

The Effect of Freight Rates on Fleet Productivity: An Empirical Research on Dry Bulk Market

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Abstract

Fleet productivity increases in two directions. First one is achieved by increasing the speed of the vessels in the market conditions where high freight rates are observed, this increases the amount of cargo per unit capacity they carry at the unit time. The other one is related to the short run inelastic supply curve in shipping because of the time to build effect. When the demand increases occur, the amount of cargo carried per unit capacity increases since the increase in supply is limited in the short run. In this context, it is determined the relationship between freight rates and the amount of cargo carried per unit capacity in this study. The Baltic Dry Index (BDI) was selected as a measure of the freight rates, and the tonnage carried per DWT from the portion of the total cargo tonnage carried by the sea to the dry cargo fleet capacity during that year was selected as an indicator of the fleet productivity. The dataset used in the study consists of annual observations covering the period from 1985 to 2020. Correlation and regression methods were used to determine the econometric relationship between the variables. As a result of the study, a significant strong relationship was found between freight rates and productivity in the positive direction. According to the developed model, a 10% increase in the freight rate causes an increase of about 1.3% in fleet productivity.

1. Introduction

Maritime transport is today still the most efficient way for transporting larger volumes of cargoes in an acceptable price across the oceans and without maritime transport, the development of the modern industrialized world would be impossible (Heidbrink, 2011; 49). Despite this important role, the maritime market is sensitive to macroeconomic conditions. Because, the demand for shipping services is a derived one and the main driver behind this derived demand is the world merchandise trade (Tamwakis, 2011; 52). So, even small fluctuations in the world economy are strongly felt in this market. Therefore, the effective use of the maritime fleet, which is the capital of the shipowners, varies according to the situation in the economy.

In general, the productivity of the fleet may increase due to two reasons; the first is the increase in demand for maritime transport due to revival in the economy and the second is the increase in the short-term transport capacity by increasing ship speeds (Karakitsos and Varnavides, 2014; 43). Both of which are mainly due to inelastic short-run supply curve in the maritime market. In addition to these, factors such as the increase in the average size of the ships, the developments in cargo handling speed in the ports, the opening of alternative waterways also affect the productivity of the fleet (Ma, 2020; 121). In addition, another productivity factors are the amount of cargo and navigating distance in the context of the productivity of shipping in relating to fleet productivity. So, shipping productivity can be affected by various factors such as economy, politics, geographical borders, war, and weather conditions, etc. (Duru, 2010; 167). However, in this study, we focused more on two factors, which are demand increase and speed increase, due to data constraints and simplification of the relationships.

It would be useful to first address the inelastic supply curve in the short run. The supply of shipping services can be categorized as short-run and long-run. If the stock of the fleet is fixed, it is called short-run, if the stock of the fleet is variable, it is called long-run (Karakitsos and Varnavides, 2014; 42). As can be seen in Figure 1, the freight rates are elastic until the 80% of the fleet up to the point of use, but when the next 20% of the limit is passed, it

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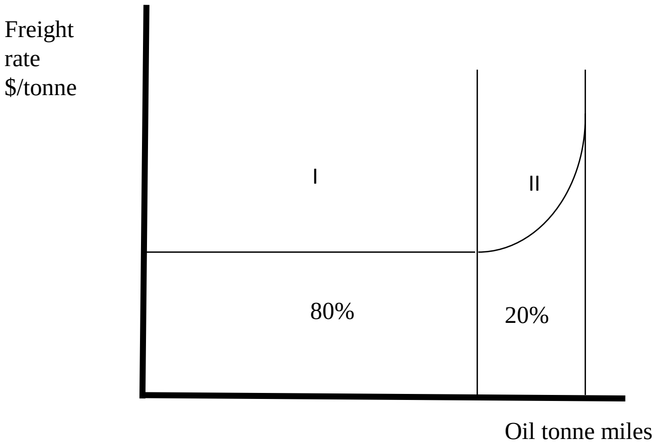
begins to become inelastic, and freight demanded by shipowners starts to increase rapidly (Glen and Christy, 2010; 379). The other version of this model, including demand lines, is presented in Figure 2.

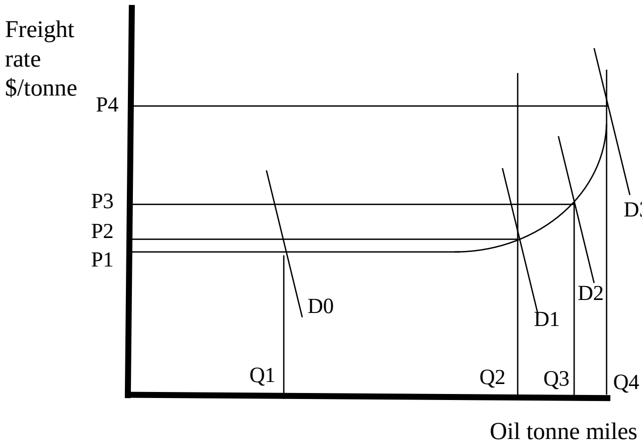
Figure 1. Short Run Supply Curve for Shipping Services



Source: Glen and Christy (2010; 379).

According to Figure 2, there is an insignificant increase in freight rates from P_1 to P_2, although there is a very large increase between D_0 and D_1. Later in the upright, a small increase in the amount causes a large increase in freight, for instance, when there is an increase from D_2 to D_3, freight rates increase much more from P_3 to P_4 (Glen and Christy, 2010; 381). This situation is a result of the fixed capacity of the fleet in the short run. Since shipbuilding times can vary between 1 and 4 years on average depending on factors such as ship type, congestion in shipyards, freight market conditions, the supply of new ships to the market remains limited (Tsolakis, 2005). This situation causes the freights to increase very much even with the slight increase in demand. This causes the freight markets to follow continuous cycles and be very volatile (Stopford, 2009; 104). Although these volatilities may seem like a disadvantage, they also provide important profit opportunities for ship owners.

Figure 2. Modeling Shipping Demand and Supply in the Short Run

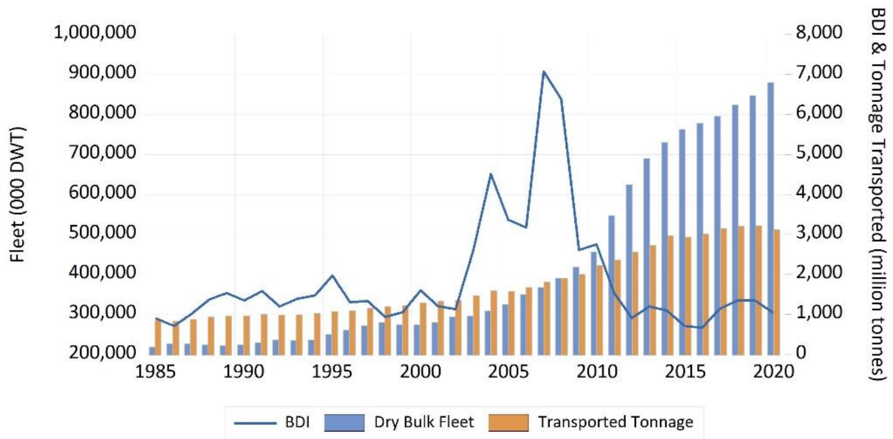


Source: Glen and Christy (2010; 381).

Due to this inelastic supply curve, there is an increase in freight rates in case of demand increase. At this point, it is inevitable that this increase in demand will also increase the transportation productivity of the fleet. In addition, ship owners who wish to benefit more from higher freight rates increase their voyage speeds, since lower speed means less cargo is delivered (Stopford, 2009; 244). This further increases the amount of cargo carried per unit time per dwt since the bunker cost from the speed increase may be lower than the freight income from carrying more cargo. According to all these, it is quite natural that there is a positive relationship between fleet productivity and freight rates.

The graphical representation of the dataset used in the analysis is presented in Figure 3 and was thought to facilitate the understanding of the above-mentioned relationship. The graph includes the fleet, the tonnage carried and the BDI variables. When the tonnage carried is considered as demand, it is clearly seen how the difference between the supply (fleet) and demand has been opened after 2008. Of course, many factors affect freight rates, however this difference between supply and demand has also caused a sudden collapse in freight rates due to the oversupply in the market. This difference is also mathematically indicative of a decrease in the amount of cargo carried per dwt (productivity). Hence, a positive relationship between fleet productivity and freight rates is inevitable. However, no study employing empirical test for this relationship has spotted in the literature. This lack has also generated the motivation for this study. There are studies that indirectly support this relationship rather than directly modeling the issue. A limited number of studies have been conducted that have identified a positive relationship between world GDP and freight rates (e.g. Başer and Açık, 2019; Akbulaev and Bayramli, 2020; Michail, 2020; Özer et al., 2020; Efes, 2021), and a positive relationship between freight rates and ship speed (Wen et al., 2017; Açık, 2021). In both cases, productivity will increase as freights increase due to higher demand and ship speeds increase due to higher freight rates. Therefore, the relationship between freight rates and productivity is inevitable.

Figure 3. Transported Tonnage, Dry Bulk Fleet and BDI Variables



Source: UNCTAD (2021); Bloomberg (2021).

The fleet productivity can be tracked in several ways. Some of these measurements are ton-miles performed per dwt and tonnage carried per dwt. For the fleet productivity measurement in this study, the total amount of dry bulk cargo carried in the world and the dry bulk fleet volume variables were used due to the data limitation. The cargo carried was divided into the fleet volume and the amount of cargo carried per dwt was obtained, and so the fleet productivity variable was generated. For freight rates, BDI variable, which has become one of the primary indicators on the cost of shipping in the world since its establishment (Lin and Sim, 2013) and has reflected the changes in dry bulk freight transport as a component indicator (Angelopoulos, 2017), was used. In the model established, other factors affecting the freight rates were assumed to be fixed in order to be able to see the relationship between the two variables clearly. As a result of the research, the relationship between freight rates and fleet productivity was empirically tested and the positive relationship was confirmed. Thus, the relationship, which has been theoretically discussed many times in the literature, has been empirically tested and verified. As a result, it is recommended that fleet expansion policies be at a more sustainable level for both ship and cargo owners, as the difference between demand and supply growth rates directly affects fleet productivity and hence transport costs.

The remainder of the study was organized as follows; the methods used in the study were introduced in section two; the results obtained from the analysis were presented in section three; then lastly, the findings were interpreted and discussed in the conclusion section.

2. Methodology

The methodology used in the study consist of two methods; correlation analysis and regression analysis. Correlation analysis was used to determine the direction and strength of the relationship, and a regression analysis was used to determine the causal relationship. Both methods are briefly introduced in the following sections. The method section should be added here, after that subsections (second and third level headings), if any, should be included.

2.1. Correlation Analysis

Correlation analysis helps us determine the degree of the relationship between two or more variables (Sharma, 2005:3). The correlation does not show causality but shows the direction and strength of the movements of the variables. Correlation coefficients range between 1 and -1, and coefficients equal to 1 or -1 means that data points lying exactly on a straight line (Chang, 2014; 78). Two methods are used for correlation calculations; Pearson's correlation and Spearman's correlation. While the two methods give similar results, their use varies according to the distribution of the variables. Pearson correlation coefficient assumes that the data are normally distributed while Spearman correlation can be used in circumstances where data investigation is not normally distributed (Osborne, 2008; 39).

Evaluation of the correlation analysis depends on the degree and direction of the correlation coefficient. The closer the absolute value of the correlation coefficient is to 1, the stronger the relationship. Generally, correlation coefficients are classified into 5 groups; the coefficient between 0.00-0.20 is called very weak; the coefficient between 0.20-0.40 is called weak; the coefficient between 0.40-0.60 is called moderate; the coefficient between 0.60-0.80 is called strong; and lastly, the coefficient between 0.80-1.00 is called very strong (Soh, 2016; 40).

Although correlation analysis is simple, it is a useful method and has been used as a research method in some studies dealing with the BDI variable. When the correlation analyzes about the BDI are examined in the literature, several studies are found in which different factors are examined as indicated in Table 1.

Table 1. Correlation Analysis used with BDI

Authors	Variables Associated with the BDI	Findings
Ruan, et al. (2016)	Crude oil prices	Cross-correlations between BDI and crude oil prices are significantly multifractal.
Kärrlander, (2010)	MSCI metals and mining index	There is a statistically significant correlation between BDI and the MSCI metals and mining index.
Xiong and Hu (2021)	Chinese soybean prices	There is a very low correlation between BDI and Chinese soybean prices.
Derindere Köseoğlu, (2011)	GDP	There is a positive correlation between BDI and world GDP between the years of 1986 and 2008.
Bakshi, et al. (2011)	Global stock returns, commodity returns, and industrial production growth	There is a significant relation between BDI and subsequent global stock returns, commodity returns, and industrial production growth.

Correlation analysis is a useful method; however, it is insufficient to explain how much a change in one variable causes a change in another variable. One of the most basic methods to answer this question is regression analysis. Therefore, we preferred regression analysis in addition to correlation analysis in the research.

2.2. Regression Analysis

Regression analysis aimed at discovering how one or more variables affect other variables. The affected variables are called dependent or response variables while affecting variables are called independent variables, predictor variables or regressors (Sen and Srivastava, 1990; 1). Regression analysis allows researchers to quantify how the average of one variable systematically varies according to the levels of another variable (Gordon, 2015; 5).

The following equation (1) shows the contents of a simple linear regression. The dependent variable is represented by Y_t, while independent variable represented by xi. β_0 and β_1 variables are the coefficients of the equation. β_1 gives the slope of the regression line, and if it is positive, it indicates a relation in the same direction, otherwise it indicates a relation in the opposite direction. The part unexplained in the model is aggregated into ϵ_t and forms the error terms of the model. Error terms are important for the process of developing consistent and unbiased regression models. So that after the model is estimated, there are many tests on the error terms.

$$y_t = \beta_0 + \beta_1 x_t + \epsilon_t \quad (1)$$

3. Findings and Results

Descriptive statistics of the data used in the study are presented in Table 2. The first two columns of the table belong to the "loaded tonnage" and "fleet" values used in the productivity calculation. Loaded cargo tonnage is divided by the total fleet to reach transported ton value per dwt during the year. That is, equation (2) was used and the productivity value (ton per dwt) was obtained.

$$Productivity = \frac{Transported\ Cargo}{Fleet} \qquad (2)$$

The descriptive statistics of the Baltic Dry Index, another variable used in the study, are also included in the table. The BDI and productivity variables were used in econometric analysis in the direction of the study, so logarithms were taken in advance. Taking logarithms of the variables makes discrete data continuous and facilitates processing of the data. Then, the unit root test was performed on logarithmic variables and the results are presented in Table 3.

Table 2. Descriptive Statistics for Raw and Converted Data

	Loaded (Million tons)	**Fleet (000 dwt)**	**BDI**	**Prod**
Observations	36	36	36	36
Mean	1742.389	1742.389	1855.269	4.322947
Median	1413.500	1413.500	1352.720	4.302556
Maximum	3218.000	3218.000	7070.256	5.136999
Minimum	834.0000	834.0000	673.1200	3.545880
Std. Dev.	826.5914	826.5914	1458.558	0.412472
Skewness	0.655624	0.655624	2.331261	0.176528
Kurtosis	1.908704	1.908704	8.004411	2.084102
Jarque-Bera	4.365447	4.365447	70.17486	1.445277
Probability	0.112734	0.112734	0.000000	0.485470

Source: Bloomberg (2021); UNCTAD (2021).

In the time series analyzes, deviations and inconsistencies arise in estimates in the case of the series containing the unit root. For this reason, the Augmented Dickey-Fuller (Dickey and Fuller, 1969) unit root and KPSS (Kwiatkowski et al., 1992) stationarity tests were applied to BDI and productivity variables and the results are presented in Table 2. According to the ADF test, the unit root null hypothesis was rejected at the level for both variables. The KPSS test was also applied as a supporting test and the null hypothesis of the test indicates that the series are stationary. The results show that the null hypothesis is accepted, and, unlike the ADF test, the series are stationary in level. Since difference taking operations in series can cause loss of information, we hereby decided that the series are stationary based on the results of the KPSS test. Therefore, the series are I (0). After this phase, correlation analysis was started to determine the directional relationship between the variables.

Table 3. Unit Root and Stationarity Test Results

		Level		**First Difference**	
Test	**Variable**	**Intercept**	**Intercept & Trend**	**Intercept**	**Intercept & Trend**
ADF	BDI	-2.09	-2.01	-2.84*	-2.84
	Prod.	-0.78	-0.79	-5.00***	-5.96***
KPSS	BDI	0.13*	0.12**	0.10*	0.04
	Prod.	0.19*	0.19***	0.45**	0.08*

ADF CVs -3.65 for ***1%, -2.95 for **5%, -2.62 for *10% at Intercept, -4.27 for ***1%, -3.56 for **5%, -3.21 for *10% at Trend & Intercept. Schwarz automatic lag selection was used at maximum 3 lags. KPSS CVs 0.74 for ***1%, 0.46 for **5%, 0.35 for *10% at Intercept, 0.22 for ***1%, 0.15 for **5%, 0.12 for *10% at Trend & Intercept. Barlett Kernel spectral estimation method and Newey-West bandwidth were used.

Correlation analysis was used to determine whether there was a directional relationship between the movements of the variables. The different analysis method applied according to the distributions of the variables. When Table 1 was examined, it was determined that both of the Ln BDI variable and the Ln Productivity variables were normally distributed. Thus, Pearson method was more suitable but both Pearson and Spearman analysis methods were used, and results are presented in Table 4. According to the results, significant strong degree correlations were found between the two variables in the positive direction. But this analysis only shows the direction and strength of the relationship, but not the causal relationship, therefore, a regression model was adopted.

Table 4. Results of the Correlation Analysis between Variables

	Ln BDI	
	Pearson	**Spearman**
Ln PRODUCTIVITY	0. 7929 (7.588) 0.0000*	0.7958 (7.664) 0.0000*

Significance levels = * 1%

The regression model of our study was presented below. The BDI, which is the independent variable, represents the revenues of the shipowners, and the dependent variable is the PRODUCTIVITY reflecting the transferred tonnage per dwt in the fleet. The hypothesis we have established is that there is a positive relationship between shipping revenue and productivity. Then, the model was established and predicted this way.

$$LnPRODUCTIVITY_t = Ln\beta_1 + \beta_2 LnBDI_t + \varepsilon_t$$

The results of the estimated regression analysis are presented in Table 5. According to the results, the F statistic indicating the significance of the model is significant at 1% confidence level (0.000003<0.01), and the independent variable BDI is also significant at %1 confidence level. The coefficients of the model show the elasticity of the productivity with respect to the revenue, and according to the results, the 1% increase in the revenue causes an increase of 0.133% in the productivity. R-squared value showing the explanatory power of the model is relatively low, but it is good for the differenced variables used models. The value is 62, which means that 62% of the changes in the dependent variable are explained by the independent variable. On the other hand, this moderate value may be due to the irrelevance of the selected variables, or structural break and outliers in the model may decrease explanatory power. Thus, it is useful to examine some stability tests and graphs from the regression equation.

Table 5. Regression Equation Results of Model

Dependent Variable: Ln PRODUCTIVITY				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.4828	0.1290	3.7406	0.000*
Ln BDI	0.1331	0.0175	7.5888	0.000*
R-squared	0.6287	F-statistic		57.5913
Adjusted R-squared	0.6178	Prob (F-statistic)		0.000*

Significance levels = * 1%

We first looked at the actual, fitted, residual graph showing the relationship between the estimated value and the actual value. It was included in the appendix section, and according to the graph, there were small deviations but no big deviation were spotted, which means our model fits well. The second visual we examined is the influence statistics and according to these statistics deviations did not exceed the critical value so much and there were no large deviations that could be solved with the dummy variables. All these graphs are presented in the appendices. All of these tests indicated that the model fitted well satisfactorily.

Some tests are applied to residuals of the model to test the stability of the model in regression estimations. The most important of the conditions that the residuals must provide for the model to be consistent and stable are no autocorrelation, no serial correlation, homoscedasticity and normal distribution. The Ljung & Box (Ljung and Box, 1979) test for autocorrelation was performed and the results are presented in Table 6. The null hypothesis of this test is that there is no autocorrelation in the residuals and according to the results the null hypothesis was rejected in all 16 lags.

Table 6. Autocorrelation and Partial Correlation Check for the Residuals of the Model

Lags	AC	PAC	Q-Stat	Prob	Lags	AC	PAC	Q-Stat	Prob
1	0.709	0.709	19.649	0.000	9	-0.011	0.158	29.813	0.000
2	0.439	-0.129	27.390	0.000	10	0.020	-0.025	29.833	0.001
3	0.216	-0.089	29.327	0.000	11	0.085	0.100	30.227	0.001
4	0.077	-0.011	29.581	0.000	12	0.072	-0.110	30.522	0.002

5	0.030	0.050	29.619	0.000	13	-0.063	-0.208	30.759	0.004
6	-0.006	-0.046	29.621	0.000	14	-0.255	-0.248	34.818	0.002
7	-0.012	0.014	29.628	0.000	15	-0.317	0.110	41.366	0.000
8	-0.061	-0.101	29.807	0.000	16	-0.365	-0.208	50.459	0.000

The results of the remaining tests are presented collectively in Table 7. The LM test is used for the serial correlation test and the null hypothesis is that there is no serial correlation. The null hypothesis in our model was rejected according to the F statistic used in small samples. The white test (White, 1980) was used for the heteroscedasticity in the residuals and the null hypothesis of this test is that there is no heteroscedasticity. According to the results the null hypothesis could not be rejected and the residuals were homoscedastic. The final test is the Jarque-Bera test, which tests whether the residuals are normally distributed, and the null hypothesis of this test is that the residuals are normally distributed.

Table 7. Robustness Checks for Residuals of the Model

Test Name	**Results**			
Breusch-Godfrey Serial Correlation LM Test	F-statistic	27.31832	Prob. F(2,32)	0.0000
	Obs*R-squared	22.70309	Prob. Chi-Square(2)	0.0000
Heteroskedasticity Test: White	F-statistic	0.119089	Prob. F(3,27)	0.8881
	Obs*R-squared	0.257968	Prob. Chi-Square(3)	0.8790
	Scaled explained SS	0.251892	Prob. Chi-Square(3)	0.8817
Jarque-Bera Normality Test	Skewness	-0.0840	Jarque-Bera	0.0962
	Kurtosis	3.1893	Probability	0.9530

According to the results of the tests we applied to the residuals of the model, autocorrelation and serial correlation problems were determined. For this reason, the standard errors were recalculated by re-running the model with the HAC (Newey and West, 1987) covariance estimation method, and the results are presented in Table 8. The new results indicated that there was no change in the significance of the variables in the model, and a 1% change in freight rates causes a 0.13% change in productivity of the fleet.

Table 8. Regression Equation Results of Robust Model

Dependent Variable: Ln PRODUCTIVITY				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.4828	0.1449	3.3314	0.0021*
Ln BDI	0.1331	0.0188	7.0473	0.0000*
R-squared	0.6287	F-statistic	57.5913	0.000*
Adjusted R-squared	0.6178	Wald F-stat.	49.6653	0.000*

Significance levels = * 1%

4. Conclusion

The operational behavior of commercial ships is basically shaped by the balance between supply and demand. In cases where the demand is high, the ships may want to increase their work per unit time by increasing their speed since the freights are high. Because in such an environment, the cost incurred by increasing the speed is lower than the gain obtained by carrying more cargoes. Thus, more cargo is carried per unit time. On the other hand, ships rarely sail fully loaded. According to this measurement called the fleet utilization rate, the utilization rates of the ships vary a lot. Especially in recent decades, flexibility in cargo selection has decreased due to the specialization of ships. Ships specialize in certain cargoes to reduce per unit transportation cost. Thus, it is no longer possible to carry cargoes of different types in a single ship type. As a result, the increase in demand can positively change the amount of cargo carried per unit time by affecting both the speed of the ships and the utilization rates of the specialized ships. The increase in demand is felt in the market, reflected in the freights, as maritime transport has a derived demand structure. Thus, the positive relationship between fleet productivity and freight rates is clearly evident when the literature is examined, but no empirically tested study has been spotted. So, in this study it was tried to test the econometric significance of this relationship and it was contributed to the literature by using limited dataset.

The variable obtained from the portion of the total carried dry bulk to the total fleet capacity was used as a productivity variable. The result gave us the amount of dry bulk cargo carried per dwt. For the freight rate variable, the BDI value converted to the annual data is used by taking the average of the daily values of the index. By this way, the data set was formed by annual observations covering the years 1985 and 2020. For the determination of the econometric relationship, correlation and regression analysis was performed. As a first step in the application, it was determined that the series were stationary according to the implemented unit root analysis. This can be interpreted as the series carry the shocks they are exposed to temporarily and tend to return to their average values in the long run. Then, a positive relationship between the two variables was confirmed according to the obtained results by using econometric analysis. Correlation analysis showed strong positive significant correlations (0.792 and 0.795) between the two variables. Regression analysis showed that the 1% increase in the revenue causes an increase of 0.13% in productivity, and according to the R-squared value, 62% of the changes in the dependent variable (productivity) is explained by the independent variable (freight rate).

In the literature, there is no empirical study that directly examines the relationship between productivity and freight rates. However, in parallel with our results, there are studies confirming the positive relationship between GDP and freight rates. There are studies in this direction for several maritime markets (e.g. Başer and Açık, 2019; Akbulaev and Bayramli, 2020; Michail, 2020; Özer et al., 2020; Efes, 2021). As a simple logic, the increase in economic activities also increases the demand for maritime transport, causing an increase in freight levels. This rise is due to the shortage of supply in the supply-demand balance. In such a case, the utilization rates of the ships increase, and their productivity also increases. On the contrary, as the demand for maritime transportation decreases, ship utilization rates decrease and productivity decreases. In addition, it has been determined in the literature that freight rates positively affect the speed of ships while modeling ship speeds (Wen et al., 2017; Açık, 2021). Of course, such a situation arises with the effect of increasing freight rates after increasing demand. Due to the speeding ships, the cargo carried per unit time increases, and therefore the productivity increases. Our study forms a complementary structure with these studies and deals with the same story from different angle.

It is seen in the research that there is a strong positive relationship between the productivity of the fleet and the freight level in the market. In this case, according to the balance of supply and demand in the market, while the increase in productivity causes the transfer of extra resources from the cargo owners to the ship owners, the decrease in productivity may cause the transfer of extra resources from the ship owners to the cargo owners. Like a zero-sum game, this may cause losses between the parties, depending on market conditions. In this respect, the surplus resources paid also affect the welfare level of society, as they also affect the export and import costs of the countries. As a result, more sustainable implementation of fleet expansion investment policies can contribute to a more predictable freight market condition. This uncertain situation can be brought under control by applying some regulations to the dry bulk market, which is prone to perfectly competitive conditions.

One of the most important limitations of the study is the annual frequency of the data. Better results could be obtained with more frequent data sets. Further studies may examine this relationship in other maritime markets such as liquid bulk and container. In addition, other factors affecting freight rates can be added to the model, and the model can be varied.

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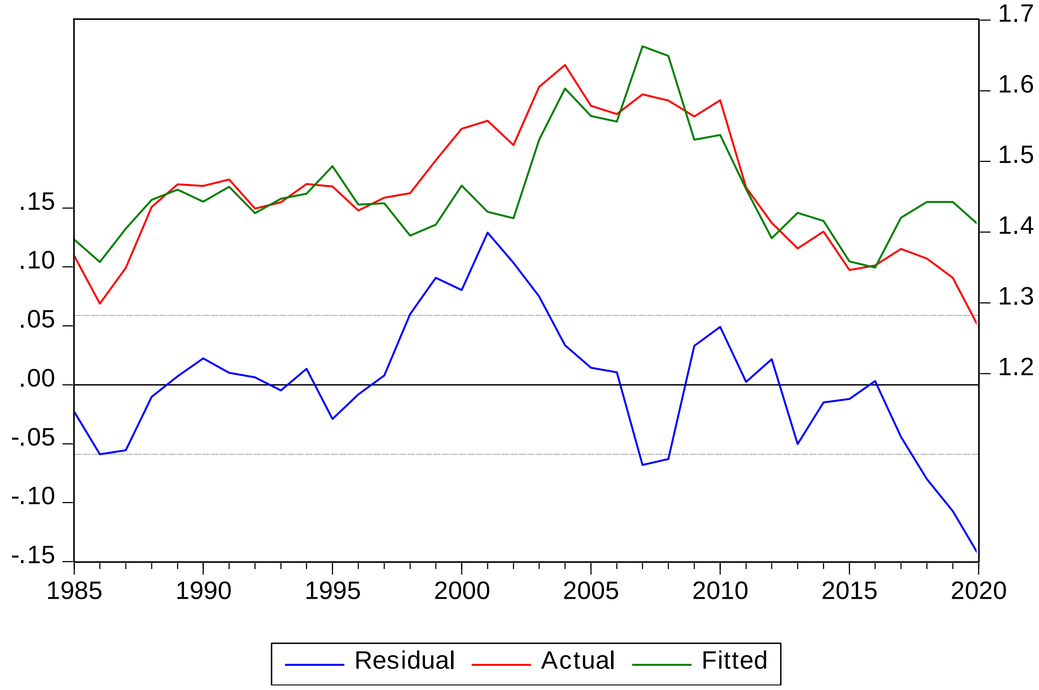
Appendices

Appendix 1. Actual, Fitted and Residual Values of the Model



Appendix 2. Influence Statistics of the Model