MABR
6,3

The interrelationship between ocean, rail, truck and air freight rates

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Received 3 August 2020
Revised 19 February 2021
19 May 2021
Accepted 21 May 2021

Abstract

Purpose – The purpose of this paper is to examine the long-term cointegrating relationship between ocean, rail, truck and air cargo freight rates, as well as the short-term dynamics between these four series. The authors also test the predictive ability of these freight rates on major economic indicators.

Design/methodology/approach – The authors employ a vector error-correction model using 16 years of monthly time series data on freight rate data in the ocean, truck, rail and air cargo sectors to examine the interrelationship between these series as well as their interrelationship with major economic indicators.

Findings – The authors find that truck freight rates and as well as dry bulk freight rates have the strongest predictive power over other transportation freight rates as well as for the four major economic indicators used in this study. The authors find that dry bulk freight rates lead other freight rates in the short-run but lag other freight rates in the long run.

Originality/value – While ocean freight rate time series have been examined in a large number of studies, little research has been done on the interrelationship between ocean freight rates and the freight rates of other modes of transportation. Through the use of data on five different freight rate series, the authors are able to assess which rates lead and which rates lag each other and thus assist future researchers and practitioners forecast freight rates. The authors are also one of the few studies to assess the predictive power of non-ocean freight rates on major economic indicators.

Keywords Cointegration, Time series, Air freight rates, Ground freight rates

Paper type Research paper

1. Introduction and conceptual framework

Prior research has suggested that ocean freight rates may be leading indicators of stock prices (Apergis and Payne, 2013; Manoharan and Visalakshmi, 2019), economic growth (Ghiorghe and Gianina, 2013; Bildirici *et al.*, 2016) and many other factors such as exchange rates (Han *et al.*, 2020). Given that ocean freight account for as much as 90% of global trade (Telford and Bogage, 2021), the strong interest among researchers in the predictive potential of ocean freight rates is not surprising.

Most of these studies have used the Baltic Dry Index (BDI) as their measure of ocean freight rates, which is an index of global dry bulk shipping rates. Potential reasons given for the BDI's role as a predictor of future economic activity include its status as an index of raw material demand which captures activity at the very beginning of production, as well as it being an indicator of international trade (Köseoğlu and Sezer, 2011). Other reasons have included that BDI is not as subject to speculation as other indicators such as stock and bond prices and not as subject to government manipulation as economic indicators such as unemployment and inflation (Köseoğlu and Sezer, 2011).

In spite of the positive results for the BDI found in prior studies, some have noted its limitations as a predictor. Inelastic supply (Bakshi *et al.*, 2012), long-term charters (Rehmatulla *et al.*, 2017) and a lack of competition in some markets (Adland *et al.*, 2016) may make dry bulk freight rates slow to respond to market trends. By contrast, the trucking industry is highly

Maritime Business Review
Vol. 6 No. 3, 2021
pp. 256-267
Emerald Publishing Limited
2397-3757
DOI 10.1108/MABR-08-2020-0047

fragmented with 90% of carriers having fewer than six trucks (Medwell, 2016) and 99% having fewer than 50 trucks (Browne, 2020). Freight rates in more competitive transportation sectors may be quicker to respond to economic trends and hence make better predictors. However, little research has been done to examine the predictive power of other transportation freight rates besides the BDI.

Only limited research has been done on the predictive power of freight rates other than the BDI. Hsiao *et al.* (2014) find that freight rates are an effective predictor of the BDI, but only during an economic downturn. They attribute to the BDI being an indicator of demand for raw materials and container freight rates reflecting demand for finished goods, with each signalling different stages of the business cycle. Li *et al.* (2018) find that clean tanker freight rates predict dirty tanker and container freight rates but not vice versa. Michail and Melas (2020) point to the fact that clean tankers can be converted to dirty tankers but not vice versa as a possible explanation for the differing dynamics between these rates. If it is true that different ocean freight rates each possess different information about future market trends, it may also be argued that non-ocean freight rates may also possess different but useful predictive information.

In addition to informational content, another possible mechanism by which freight rates may interrelate across modes of transportation is substitution or complement effects. For example, rail and road have been found to be relatively weak or mild substitutes in Pakistan (Khan and Khan, 2020), India (Chaudhury, 2005) and Australia (Mitchell, 2010). High cross-price elasticity between rail and road was found in the US (McCullough and Hadash, 2019) as well as high cross-cost elasticity in the European Union (Beuthe *et al.*, 2001), although more recent research found that this cross-cost elasticity has gone down in the European Union (Jourquin *et al.*, 2014; Beuthe *et al.*, 2014). One reason for the range of the results found across countries may be because truck and rail can serve as both substitutes on some routes but also as complements when trucking is used for pre- and post-haul for rail cargo (Jourquin *et al.*, 2014).

Research on cross-price or cross-cost elasticity between ground and non-ground freight transportation has been more limited and often contradictory. Coastal ocean shipping was found to be a complement to truck freight transportation but a substitute for rail in Australia (Mitchell, 2010), perhaps because rail and ocean both engage in long-distance routes, but truck can be used for last-mile shipments with ocean freight. Inland waterway shipping was found to be relatively inelastic to road transportation in the European Union, which can be attributed to the low cost of inland waterway shipping as well as the limited number of waterway routes in the European Union (Jourquin *et al.*, 2014). However, Beuthe *et al.* (2014) find a moderate degree of substitutability between road and inland waterway transportation in the European Union but no significant substitutability between rail and water. Little if any research has been done on the relationship between ground transportation and deep-sea ocean freight.

In summary, prior research on the relationship between freight rates in different modes of transportation has been limited, but there are two main mechanisms found in the literature that might explain these relationships. One is informational content, in which case freight rates such as BDI predict economic indicators or other freight rates due to it being a proxy for global economic trends rather than a direct causal impact. The other mechanism is that freight modes may be substitutes or complements for each other, with their freight rates directly impacting other freight rates by increasing or decreasing the quantity demanded for other transportation modes. In this study, we extend prior research on the predictive power of BDI on economic indicators to include freight rates for air, rail and truck freight. We also test the predictive power of air, rail and truck freight rates to see if they (like BDI) also predict economic indicators such as GDP, international trade volume and inflation.

2. Data

The primary source of data on freight rates was from the US Bureau of Labour Statistics (BLS) producer price indices for transportation freight services. We obtained monthly data on long-distance truckload (TRUCK), rail transportation of freight (RAIL), air transportation freight (AIR) and deep-sea freight (SEA). Transportation freight indices from the BLS have been used in prior transportation time series data series research, including indices of trucking freight (Miller *et al.*, 2020; Miller, 2019), deep-sea freight (Fuller and Kennedy, 2019) and air freight (Hummels, 2007). The SEA Index includes all freight between the US and foreign ports operated by US flagged ships.

The SEA Index is a broad-based index that covers all types of ocean cargo, although the US fleet involved in international trade has a heavy focus on container and roll-on/roll-off transportation with very few tankers (Fritelli, 2015). A limitation of the SEA Index is that it only covers the US flagged international fleet which consists of 80 ships (Fritelli, 2015). Due to the limitations of this index, we also use the BDI as a second measure of deep-sea ocean transportation. This is a widely used index of dry bulk freight rates created by the Baltic Exchange. An advantage of this index is that it measures to market rates of the entire global dry bulk industry, not just a single country's carriers. However, it is limited in that it only covers dry bulk shipping. The combination of the two indices covers two different ends of the ocean freight market.

The BDI is a global measure of the market rate for dry bulk transportation and hence operates as a consumer price index (CPI), whereas the other freight series are producer prices indices (PPI). However, cabotage laws and other market conditions may make the distinction between the CPI and PPI relatively small. For example, not only are US truck carriers protected from competition on domestic routes but they also have considerable protection on cross-border routes (Abbot, 2020). US-Mexico rail routes are also heavily controlled by US rail carriers (Redaccion Opportimes, 2020). So overall there is unlikely to be a large difference between what US consumers are paying for these transportation services and what US producers are charging.

Figure 1 shows the time trends for all five freight rate series. Since BDI is measured in different units than the BDI, all series are adjusted for purposes of the graph so they all start at 100 at the beginning of the series. We can see the BDI is far more volatile than the other series, but it becomes more stable after 2010. The SEA Index is much less volatile than the BDI but also trends lower than the other indices and trends upwards towards the end.

In addition to the freight rates, additional economic indicators were included for additional analysis. Two indicators of transportation cost trends were included – crude oil prices (CRUDE) and the US consumer price index (CPI). The monthly CPI data came from the OECD and monthly crude oil prices come from the International Monetary Fund. Prior research has shown that the CPI can predict the BDI (Lyridis *et al.*, 2014) and that in turn the BDI can

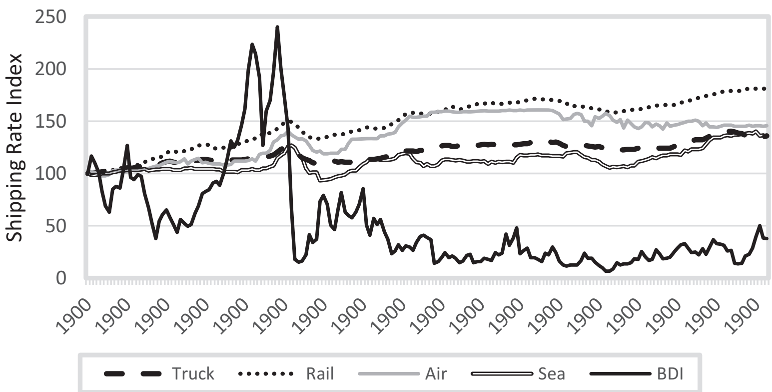

Figure 1.
Transportation freight rate indices 12/2003 to 10/2019

predict inflation (Han *et al.*, 2020). Two indicators of freight transportation demand were used, GDP and US international trade volume (total US imports and exports or TRADE). The monthly GDP data were obtained from IHS Markit, a private analytics firm whose monthly GDP index has been used in prior recent studies (Hoda *et al.*, 2020; Soon and Thompson, 2019). Finally, the import and export data were obtained from the US Census Bureau.

Table 1 presents the summary statistics of the nine series. All statistics are based on logged first differences of the variables, or approximate monthly percentage changes. All five freight rate series have similar properties, although the two ocean freight series BDI and SEA have kurtosis greater than seven, indicating a lack of a normal distribution. BDI has the highest standard deviation and is also the only series with a negative trend. The remaining four economic indicators have generally similar properties to the non-ocean freight rates, although CRUDE has a higher standard deviation of 0.088.

3. Methods and results

3.1 Diagnostics

To assess causal direct between our freight series, we use the method of Granger causality (Granger, 1969) and cointegration (Engle and Granger, 1987). As the first step in this analysis, we test for stationarity for all of our variables the Phillips and Perron (PP) (1998) test and the Dickey-Fuller generalized least squares (DFGLS) (Elliot *et al.*, 1996) test to assess non-stationarity in logged levels of our five series. None of the test statistics are significant at the 5% level for either the PP or DFGLS test. Thus, we cannot reject the null hypothesis of a unit root and we can presume the series are non-stationary (Harvey, 2005). For first differences, the null hypothesis of a unit root is rejected for all five series, indicating stationarity of all series when using the PP test. However, for the DFGLS test, the null hypothesis of a unit root cannot be rejected for first differences of lnGDP. However, much prior literature has shown that GDP first differences are stationary (Kim, 2018; Mitic *et al.*, 2017). Based on these results, the use of first differences in our analysis is indicated as the use of levels may lead to spurious results (Lin and Brannigan, 2003).

No clear consensus exists in the literature regarding the best method to select the optimal lag length. Liew (2004) recommends the final prediction error (FPE) and the Akaike information criteria (AIC) as the most accurate way to choose lag length. However, Hatemi-J and Hacker (2009) find that the combination of the Hannan–Quinn information criteria (HQIC), the Schwarz Bayesian information criteria (SBIC) and the likelihood ratio (LR) provides the best lag length decision. Using all of these methods gives us a median of two lags which we use for the analysis.

Variables	Obs	Mean	Std. Dev	Minimum	Maximum	Skewness	Kurtosis	Source
AIR	190	0.002	0.017	−0.054	0.012	0.242	5.07	BLS
BDI	190	−0.005	0.255	−1.330	0.671	−1.058	7.279	Baltic exchange
RAIL	190	0.003	0.008	−0.028	0.027	−0.243	4.885	BLS
SEA	190	0.002	0.017	−0.019	0.041	−1.402	11.571	BLS
TRUCK	190	0.002	0.007	−0.029	0.023	−0.68	5.758	BLS
CPI	190	0.002	0.004	−0.019	0.012	−1.197	7.145	BLS
CRUDE	190	0.003	0.088	−0.341	0.219	−0.988	4.885	IMF
GDP	190	0.002	0.005	−0.018	0.017	−0.301	4.06	IHS Markit
TRADE	190	0.004	0.033	−0.142	0.094	−0.237	5.068	US Census Bureau

Note(s): BDI is Baltic Dry Index, SEA, AIR, RAIL and TRUCK are BLS transportation freight indices, CPI is the BLS consumer price index, CRUDE is crude oil prices, GDP is monthly US GDP amd TRADE is total monthly imports and exports

Table 1. Descriptive statistics of logged monthly changes

3.2 Base model

Our initial analysis starts with a base model with only the indices of freight transportation, using methods of a vector error-correction model to assess both short-run dynamics between freight rates through Granger causality (Granger, 1969) and cointegration (Engle and Granger, 1987; Johansen, 1988). As a start, we examine whether there is a stable, long-term relationship between freight rates by testing for cointegration. We use the Johansen (1988) cointegration test and find that significant cointegration is found when lnBDI is used as our measure of ocean freight but not when lnSEA is substituted for lnBDI. Hence analysis for lnBDI was done using a vector error-correction model, which includes an error-correction term to account for long-term effects. For regressions with lnSEA, we will use a vector autoregressive model, which allows us to examine short-run Granger causality between the freight rates and other economic variables in the absence of a detected long-run relationship (Zivot and Wang, 2007)

The existence of a cointegrating relationship for lnBDI with other freight rates means there exists a coefficient vector B such that a linear combination of the freight rates are stationary (Engle and Granger, 1987). We can express this relationship in the following equation as follows:

$$\beta_1 \mathrm{lnBDI} + \beta_2 \mathrm{lnAIR}_t + \beta_3 \mathrm{lnRAIL}_t + \beta_4 \mathrm{lnTRUCK}_t = \mathrm{ECT}_t \tag{1}$$

The coefficients represent the long-run equilibrium ratios between the four freight rates. ECT_t is the error-correction term, and it is stationary with a mean of zero if cointegration is present. Since the error term reverts to its mean of zero in the long run, it means the four freight rates must return to this equilibrium and thus cannot diverge too far from each other (Engle and Granger, 1987; Dickey *et al.*, 1991).

The Johansen (1995) maximum likelihood procedure is used to estimate the coefficients, and unlike ordinary least squares, this procedure assumes all of the variables are jointly endogenous without any assumption of a structural model (Dickey *et al.*, 1991). In order to solve for a solution, one of the coefficients needs to be normalized to one, although this does not affect the choice of $\mathrm{ECT_t}$. With lnBDI normalized to one and constant term and time trend added, we have the following equation:

$$\mathrm{lnBDI} - \beta_2 \mathrm{lnAIR}_t - \beta_3 \mathrm{lnRAIL}_t - \beta_4 \mathrm{lnTRUCK}_t - \nu - \tau^* t = \mathrm{ECT}_t \tag{2}$$

ECT_t represents the divergence from the long-term equilibrium between the freight rates, and by including ECT_{t-1} in the next set of regressions, we can examine how a divergence from the equilibrium leads or does not lead to a freight rate moving back towards equilibrium.

The rest of the regressions are intended to assess Granger causality (Granger, 1969), i.e. if changes in one of the freight rates leads to a future change in another freight rate. The independent variables are the same for all four equations with ECT_{t-1} and two lagged first differences of each freight rate. For example, ΔlnBDI is lagged one month ($\Delta\mathrm{lnBDI}_{t-1}$) and two months ($\Delta\mathrm{lnBDI}_{t-1}$). In addition to including two lags of first differences of each freight rate, first differences of each freight rate also serve as a dependent variable in one of the equations. This way the endogeneity of each freight series can be assessed one at a time, with all serving as both independent and dependent variables in different regressions. The first equation is:

$$\begin{aligned}\Delta\mathrm{lnBDI}_t = \; & \alpha_0 + \alpha_1 \Delta\mathrm{lnBDI}_{t-1} + \alpha_2 \Delta\mathrm{lnBDI}_{t-2} + \alpha_3 \Delta\mathrm{lnRAIL}_{t-1} + \alpha_4 \Delta\mathrm{lnRAIL}_{t-2} \\ & + \alpha_5 \Delta\mathrm{lnRAIL}_{t-1} + \alpha_6 \Delta\mathrm{lnRAIL}_{t-2} + \alpha_7 \mathrm{ECT}_{t-1} + \mu_t \end{aligned} \tag{3}$$

This equation estimates how lnBDI changes in response to changes in first differences in past changes in lnBDI as well as past changes in the other three series. The coefficient for ECT_{t-1}

will estimate how lnBDI will change in response to an out of equilibrium relationship between the four series. If the coefficient of ECT_{t-1} is significant, it means lnBDI lags the other series and it is the series that responds in the long-term to the other three series. The coefficients of the lagged first differences will estimate the short-term dynamics between the four series.

To see how lnAIR, lnRAIL and lnTRUCK respond to long-term deviations from the equilibrium as well as short-term responses to changes in the other series, we estimate three equations similar to Equation (2) except with first differences of lnAIR, lnRAIL and lnTRUCK as dependent variables:

$$\begin{aligned}\Delta\mathrm{lnAIR}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{lnBDI}_{t-1} + \alpha_2\Delta\mathrm{lnBDI}_{t-2} + \alpha_3\Delta\mathrm{lnRAIL}_{t-1} + \alpha_4\Delta\mathrm{lnRAIL}_{t-2} \\ & + \alpha_5\Delta\mathrm{lnRAIL}_{t-1} + \alpha_6\Delta\mathrm{lnRAIL}_{t-2} + \alpha_7\mathrm{ECT}_{t-1} + \mu_t \end{aligned} \tag{4}$$

$$\begin{aligned}\Delta\mathrm{lnRAIL}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{lnBDI}_{t-1} + \alpha_2\Delta\mathrm{lnBDI}_{t-2} + \alpha_3\Delta\mathrm{lnRAIL}_{t-1} + \alpha_4\Delta\mathrm{lnRAIL}_{t-2} \\ & + \alpha_5\Delta\mathrm{lnRAIL}_{t-1} + \alpha_6\Delta\mathrm{lnRAIL}_{t-2} + \alpha_7\mathrm{ECT}_{t-1} + \mu_t \end{aligned} \tag{5}$$

$$\begin{aligned}\Delta\mathrm{lnTRUCK}_t = {} & \alpha_0 + \alpha_1\Delta\mathrm{lnBDI}_{t-1} + \alpha_2\Delta\mathrm{lnBDI}_{t-2} + \alpha_3\Delta\mathrm{lnRAIL}_{t-1} + \alpha_4\Delta\mathrm{lnRAIL}_{t-2} \\ & + \alpha_5\Delta\mathrm{lnRAIL}_{t-1} + \alpha_6\Delta\mathrm{lnRAIL}_{t-2} + \alpha_7\mathrm{ECT}_{t-1} + \mu_t \end{aligned} \tag{6}$$

Equations (4) through (6) are highly interrelated, but since regressors are identical in each equation, it is not necessary to use seemingly unrelated regression (Zivot and Wang, 2007).

Table 2 presents the regression results from Equations (3) through (6). Table 3 presents the same equations except that ΔlnSEA is substituted for ΔlnBDI and no error-correction term is included. The main trend seen is that ΔlnBDI and ΔlnTRUCK are the best predictors

Table 2. Vector error-correction regressions with lnBDI

	Dependent variable (Equations 6 through 9)			
Regressor	(6) $\Delta\mathrm{lnBDI}_t$	(7) $\Delta\mathrm{lnAIR}_t$	(8) $\Delta\mathrm{lnRAIL}_t$	(9) $\Delta\mathrm{lnTRUCK}_t$
ECT_{t-1}	−0.266**	−0.004	−0.001	0.001
	(0.051)	(0.004)	(0.001)	(0.001)
$\Delta\mathrm{lnBDI}_{t-1}$	0.224**	0.007	0.004*	0.005**
	(0.070)	(0.005)	(0.002)	(0.002)
$\Delta\mathrm{lnBDI}_{t-2}$	0.004	−0.012*	0.004*	0.001
	(0.073)	(0.005)	(0.002)	(0.002)
$\Delta\mathrm{lnAIR}_{t-1}$	0.772	−0.080	0.081**	0.026
	(1.094)	(0.079)	(0.028)	(0.027)
$\Delta\mathrm{lnAIR}_{t-2}$	1.706	0.097	0.020	0.052†
	(1.093)	(0.079)	(0.028)	(0.027)
$\Delta\mathrm{lnRAIL}_{t-1}$	−0.867	0.222	0.170*	0.081
	(3.064)	(0.220)	(0.077)	(0.077)
$\Delta\mathrm{lnRAIL}_{t-2}$	−2.661	−0.109	−0.044	0.013
	(2.564)	(0.184)	(0.065)	(0.064)
$\Delta\mathrm{lnTRUCK}_{t-1}$	10.788**	0.657**	0.501**	0.351**
	(3.200)	(0.230)	(0.081)	(0.080)
$\Delta\mathrm{lnTRUCK}_{t-2}$	−5.487	0.100	0.211*	0.012
	(3.675)	(0.264)	(0.093)	(0.092)
Constant	−0.000	0.000	0.001**	0.001
	(0.018)	(0.001)	(0.000)	(0.000)
Adjusted R^2	0.177	0.089	0.576	0.340
Observations	188	188	188	188

Note(s): **, * and † indicate significance at the 1%, 5% and 10% level, respectively

Table 3. Vector autoregressive regressions with lnSEA

Regressor	Dependent variable $\Delta\ln SEA_t$	$\Delta\ln AIR_t$	$\Delta\ln RAIL_t$	$\Delta\ln TRUCK_t$
$\Delta\ln SEA_{t-1}$	0.135†	0.108	0.012	0.049
	(0.074)	(0.080)	(0.029)	(0.028)
$\Delta\ln SEA_{t-2}$	0.061	0.118	−0.006	−0.011
	(0.073)	(0.079)	(0.028)	(0.028)
$\Delta\ln AIR_{t-1}$	−0.032	−0.119	0.074**	0.030
	(0.069)	(0.074)	(0.026)	(0.026)
$\Delta\ln AIR_{t-2}$	−0.000	0.087	0.007	0.051†
	(0.070)	(0.075)	(0.027)	(0.027)
$\Delta\ln RAIL_{t-1}$	0.247	0.178	0.199**	0.069
	(0.197)	(0.212)	(0.075)	(0.075)
$\Delta\ln RAIL_{t-2}$	0.042	−0.148	−0.085	−0.040
	(0.171)	(0.183)	(0.065)	(0.065)
$\Delta\ln TRUCK_{t-1}$	0.133	0.396†	0.535**	0.375**
	(0.207)	(0.223)	(0.079)	(0.079)
$\Delta\ln TRUCK_{t-2}$	0.646**	−0.040	0.192*	0.050
	(0.235)	(0.253)	(0.090)	(0.089)
Constant	−0.001	0.001	0.001**	0.001
	(0.001)	(0.001)	(0.000)	(0.000)
Adjusted R^2	0.268	0.085	0.584	0.368
Observations	188	188	188	188

Note(s): **, *, and † indicate significance at the 1%, 5%, and 10% level respectively

of other freight rates as both of them significantly predict all other freight rates. ΔlnSEA and ΔlnRAIL do not have any explanatory power over other freight rates, and ΔlnAIR only significantly predicts ΔlnRAIL and ΔlnTRUCK. The regressions with ΔlnRAIL have the highest *r*-squareds which are over 0.5 in both cases, and ΔlnRAIL is significantly predicted by all other freight rates except for ΔlnSEA. ΔlnTRUCK has the second highest *r*-squared, while the lowest r-squareds are under 0.2 for ΔlnBDI and ΔlnAIR. This suggests that ground transportation freight rates are much more responsive to changes in other freight rates in other modes of transportation.

Lagged values of first differences of freight rates represent only short-term dynamics of one or two months. ECT_{t-1} on the other hand represents the deviation from an equilibrium calculated throughout the entire period covered in the data. A significant coefficient for ECT_{t-1} indicates that the dependent variable adjusts to deviations from the long-term equilibrium. Only ΔlnBDI has a negative and significant coefficient for ECT_{t-1} of −0.266, which indicates that it adjusts 26.6% closer to its equilibrium value each month. This means that it would take roughly four months for it move back to equilibrium. The other freight rates did not have significant coefficients for ECT_{t-1}, indicating that it is lnBDI that adjusts when the freight rates are out of equilibrium and not the other rates. Overall, lnBDI is only mildly reactive to short-term changes in other freight rates, but in the long-term, it is endogenous to the other freight rates.

3.3 Macroeconomic indicators

To control for other factors that might impact the demand for or cost of transportation freight services, we performed additional analysis using four different macroeconomic variables. As measures of potential demand for freight services, we included both GDP and trade volume (imports plus exports). We also included inflation (CPI) and crude oil prices as predictors of cost in the freight transportation industry. We ran four different versions each of the regressions in Tables 2 and 3, each with a different macroeconomic variable. We chose to include only one macroeconomic variable at a time for parsimony because including too many variables in a vector error-correction model increases the chance of finding more than one long-term cointegrating vector which also makes interpretation more difficult (Rahman and Mustafa, 2016).

Table 4 shows the causal directions found between each macroeconomic variable and the five freight rates. We can see that ΔlnBDI is a significant predictor of all four macroeconomic variables, and likewise it is only predicted significantly by ΔlnCPI. The only other freight rate that significantly predicts macroeconomic variables is ΔlnTRUCK, which predicts ΔlnTRADE and ΔlnGDP. ΔlnTRUCK is also significantly predicted by all four macroeconomic variables. ΔlnAIR is the least responsive to macroeconomic variables as it is only predicted by ΔlnTRADE. Of the macroeconomic variables, ΔlnTRADE is the only one that predicts all five freight rates. ΔlnCPI predicts four freight rates, and ΔlnCRUDE and ΔlnGDP each predict three freight rates.

The results from Tables 2 and 3 are generally robust to the inclusion of the four macroeconomic variables. Exceptions include the lack of a cointegrating relationship when ΔlnGDP is included in the regressions with ΔlnBDI , and that ΔlnBDI loses some predictive significance when ΔlnCPI is included. But the result that ΔlnTRUCK and ΔlnBDI are the best predictors of macroeconomic indicators is interesting in that these two freight rates are also the best predictor of other freight rates. Overall truck and dry bulk freight rates appear to possess variable information that can predict not only trends in other freight transportation sectors but also the direction of the economy as a whole.

4. Conclusion

In this study, the BDI was found to have consistent predictive power over both freight rates and economic indicators. This is consistent with the prior literature on the predictive power of the BDI on multiple economic indicators. This study confirms these prior results but also extends them by finding evidence of the BDI's predictive power for freight rates in other modes of transportation. Possible explanations for the positive relationship between past changes in the BDI and future changes in other transportation rates might be a direct substitution effect or the informational content hypothesis proposed in the literature. Given that global dry bulk shipping typically does not compete with air or ground transportation for cross-ocean transport of bulk material, the informational content explanation is more likely. Thus it appears that the BDI contains valuable information about the future direction of the transportation market, and thus can predict freight across multiple modes of transportation.

The results of this study show that TRUCK may be also a valuable predictor of freight rates as well as GDP and international trade. Future research should be done to assess the predictive power of trucking freight rates on other indicators such as stock prices and commodity prices that have previously been found to be significantly predicted by the BDI. Trucking is not a substitute for international ocean freight, so its predictive power on these

	TRADE	GDP	CPI	CRUDE
BDI	BDI → TRADE	BDI → GDP	BDI ↔CPI	BDI → Crude
SEA	SEA ← TRADE	SEA ← GDP	SEA← CPI	n/a
AIR	AIR ← TRADE	n/a	n/a	n/a
RAIL	RAIL ←TRADE	n/a	RAIL ← CPI	RAIL ← CRUDE
TRUCK	TRUCK↔TRADE	TRUCK↔GDP	TRUCK ← CPI	TRUCK ← CRUDE

Note(s): Arrows indicate that lagged first differences significantly predict the other variable

Table 4. Causal direction between freight rates and macroeconomic indicators

freight rates is likely due to informational content rather than a substitution effect. It is not clear though if the predictive power for rail and air freight rates is due to substitution or informational content, given these three modes compete for domestic freight. A limitation of this study is that only freight rates were used but not quantities shipped by each mode. Use of quantity data would help distinguish which parts of the positive relationships between freight rate movements are due to a direct substitution effect and which parts are more likely due to informational content of the freight rates.

This study has also shown that the use of different measures of ocean freight rates can give considerably different results. The BDI was shown to be a strong and consistent predictor of other variables, whereas the BLS deep-sea indicator was not predictive of other variables but was also much more sensitive to changes in other economic indicators and freight rates than the BDI. Also, BDI was shown to have a relatively consistent long-term cointegrating relationship with other freight rates, whereas the deep-sea indicator in most cases only showed a short-term relationship with the other freight rates. The high presence of container and vehicle freight in the BLS indicator may explain why it has less predictive power than the BDI as this result is consistent with the notion that dry bulk demand is a better indicator of early stages of an economic upturn than finished goods demand (Hsiao *et al.*, 2014). These differing results indicate the need for future research with additional indices of ocean freight rates such as global tanker, roll-on/roll-off and container indices. In addition to global freight rates, research should be done on freight rates for specific maritime routes, where factors such as inelastic supply and competition might be better controlled for.

While the BDI is a global index, a limitation of the study is that the rest of the freight rate data only covered the US transportation industry. The highly fragmented and competitive nature of the US trucking industry is shared by much of the world (Mortenson, 2020; Xiao *et al.*, 2020; Rodriguez, 2020), which suggests there may be potential for some generalizability of the results for the US regarding the predictive power of truck freight rates across countries. However, there are large variations in the quality of road, port, rail and air transport infrastructure across countries (Schwab, 2017). Also, dry ports in developing countries are not only less advanced but also show much different locational patterns than developed countries (Padilha and Ng, 2012; Ng and Cetin, 2012). The geography of a country is also likely to have large impacts on dynamics between different modes of transportation (Kaack *et al.*, 2018), which also limit the generalizability of this study. This shows the need for future research to assess the predictive power of transportation freight rates in countries with differing dynamics between modes of freight transportation.

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