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DYNAMIC COMMON CORRELATED EFFECT OF COVID-19 AND STOCK RETURN: EVIDENCE FROM CONTAINER SHIP INDUSTRY

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Abstract

This paper investigates the dynamic responses of stock return of container shipping companies to the global container freight indices during the Coronavirus pandemic period. The new econometric approach Dynamic Common Correlated Effects (DCCE) has been used to measure cointegrating relations among cross-sectional units. This procedure provides significant robust outcomes in the presence of cross-sectional dependence. A statistically significant and positive result has been observed between stock returns and container freight indices. The newly developed tests for a structural break were also implemented for our macro panel data. Our results are robust to structural break under different measures of container freight indices.

Keywords: COVID-19, Stock return.

1. Introduction

The outbreak of Coronavirus disease results in a significant degree of financial risk since it is a global pandemic rather than a financial crisis and the world is much more integrated than before. The World Health Organization (WHO) on March 11, 2020, has declared the novel Coronavirus (COVID-19) outbreak a global pandemic. The Dow Jones Industrial Average (DJIA) plunged with history's largest point plunged on March 9 and followed by two more record-setting point drops on March 12 and March 16. On March 12, the S&P 500 closed down -9.5%. March 2020 was the most volatile month ever. The S&P's average daily swing was 5%. The last record was from November 1929 – the average daily swing was 'only' 3.9%.

Because the virus is highly contagious and fatal, the governments imposed strict lockdowns of population, travel bans to another country, and shutdown of the bulk of manufacturing and services activity. Many industries have been directly impacted by the pandemic, especially restaurants, airlines, travel, manufacturing, and small

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business. Nevertheless, the pandemic challenged millions of businesses worldwide but also buoyed various sectors. Some so-called Coronavirus stocks – biotech, online shopping, remote education, telemedicine, and working from home - were arguably better off for it, even on the rise of delta variant. By using hand-collected data, Mazur et al. (2021) found that natural gas, food, healthcare, and software stocks earned high positive returns during the March 2020 of stock market crash.

Although extant literature has confirmed the existence of negative stock returns in previous financial crises, there is not much literature on the impact of COVID-19 on the stock markets. Xu (2021) employs a bivariate structural GARCH-in-Mean VAR in stock return and the growth rate of total COVID-19 cases to investigate the dynamic responses of stock return to the unexpected changes in the COVID-19 cases and the uncertainty associated with the pandemic in the U.S. and Canada. The empirical findings support the idea of a negative effect of an increase in the COVID-19 cases on the stock market. The stock return responses are asymmetric in the increase and decrease in the COVID-19 cases in Canada. Alternatively, stock return responses are relatively symmetric in the increase and decrease in COVID-19 cases in the US. Simon et al. (2021) investigate the impact of COVID-19 cases, CBOE volatility index (VIX index) and that of determining the impact of the VIX on major stock indexes, specifically the DJIA, FTSE100, DAX, CAC40, SSEC (China), Nikkei225, and MID. They found evidence of the cointegrating relationship between the VIX index and the COVID-19 cases. According to the fully modified least-squares (FMOLS) results, a 1% increase in the COVID-19 cases increased the VIX index by 32.5%. The facts that the unprecedented uncertainty and fear in the stock market resulted from the COVID-19 pandemic outbreak are of special importance to fund managers, risk managers, policymakers, and actuaries. Akhtaruzzaman et al.(2021)analyzed how financial contagion occurred through financial and nonfinancial firms between China and G7 countries. The VARMA DCC (dynamic conditional correlation) Garch estimated results showed that stock returns are higher between Chinese and G7 financial and nonfinancial stock returns during the COVID–19 pandemic period as compared to those during the pre-COVID–19 period. The magnitude of the increase in DCCs was higher for financial firms than nonfinancial firms, except for Germany and the US. Using Google Trends search data is used as a proxy for COVID-19 related uncertainty, Szczygielski et al. (2021) applied the ARCH/GARCH framework to measure the impact of changes in search volumes on both returns and conditional variance. The results indicated that COVID-19 uncertainty has impacted almost all regions in terms of lower returns and increased market volatility. They also demonstrated that Asian markets appear to be more resilient to COVID-19 related uncertainty.

This paper aims to investigate the relations between the stock returns of top international container shipping companies and the global container freight indices during the outbreak of the Coronavirus pandemic period. Shipping is the lifeblood of the global economy and the backbone of global trade. The shipping industry mainly refers to companies that operate maritime vessels. About 90% of world trade is carried by the international shipping industry; according to the International Chamber of Shipping. Maritime transportation is a derived demand whose main purpose is to support trade, business, and commerce. Maritime transportation focuses on four types of major maritime shipping vessels: **dry bulk carriers, oil and refined products tankers, liquified gas and chemical carrying ships, and container ships.** About 90% of non-bulk cargo worldwide is transported by container ships.[1]While many shipping companies have suffered from the COVID-19 pandemic in 2020, stocks of container liners and container-ship lessors are on the rise as resurgence in trade and strong demand for commodities in 2021. On the other hand, given the importance of the maritime shipping industry, some international freight indexes, such as Freightos Baltic Index (FBX), can be seen as the leading indicator of the direction of the global economy.[2]A rising FBX infers that demand is on the upswing and a falling FBX implies the declining demand for shipping capacity.

Several models have been employed to investigate the pandemic and stock markets, including cointegration, DCC Garch, FMOLS, and structural VAR, none of the papers employ a macro panel approach to evaluate the stock returns during the COVID-19 pandemic period. In this paper, we aim to investigate the relations between the top ten container shipping companies all over the world and the global freight equity index compiled by different sources and to find out which one is more closely related to the stock returns of individual stock during the pandemic period. Instead of focusing on the equity index of countries or regions, we specifically examine the relations between the world's top container shipping companies and the global container freight indices. This study extends the literature on stock market and structural breaks by providing insights into the COVID-19 and container shipping stock returns. The macro panel econometric technique with structural break test indicates that there exists a single structural break, which is Chinese New Year 2021, during the COVID-19 pandemic period. Further, the evidence of cross-section dependence leads to the second generation panel data estimation, namely, PANNICCA, panel cointegration, and DCCE estimators. Finally, the long-run relationship between container ship stock returns and global container freight indices seems to provide the opportunity to implement a long-short strategy during the COVID-19 pandemic period.

The remainder of this paper is organized as follows. Section 2 describes the econometric methodology. The data is presented and analyzed in Section 3 presents the results and Section 4 concludes.

[1] Container ship - Wikipediahttps://en.wikipedia.org/wiki/Container_ship
[2] FBX reflects the spot rate rates for 40-foot containers on 12 tradelines.

2. Econometric Methodology

For most macro panels, an investigation of cross-section dependence is relevant when we quantify the contribution of container ships' stock returns to the global container freight indices. In the case of the macro panel econometric technique, Zhang et al. (2019) describe the estimation procedure by using a flow chart. They indicate that the test of cross-section dependence is a prerequisite whether the panel is homogeneous (first-generation panel unit root test and first-generation panel cointegration analysis) or heterogeneous (second generation panel unit root test and second-generation panel cointegration analysis). Although they suggest that the estimation methodology for the empirical model is Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) whether the possibility of cross-section dependence exists or not. However, recently developed empirical methodology explicitly addressed the concerns of the heterogeneous panel across group members and unobserved correlation across panel members: namely, the Pesaran (2015) dynamic common correlated effects mean group estimator (DCCE), and the Augmented Mean Group estimator (AMG) introduced by Eberhardt and Teal (2010). The first generation of panel time-series estimation (FMOLS and DOLS) progressed to the second generation of panel time-series estimation (DCCE and AMG). Furthermore, as indicated by Dobnik (2011), the consideration of structural break is strongly advisable during an economic recession or financial crisis. Therefore, the present study will take into account structural breaks during the COVID-19 pandemic period. Based on the above discussions, we proceed in four steps, namely, cross-section dependence, panel unit root test, panel cointegration test, the detection of the existence of structural break, and the Ditzen (2018)'s common correlated effects (DCCE) estimators of dynamic heterogeneous panels, when analyzing how the freight indices affects sock returns.

2.1 Cross-section dependence

A large body of literature casts doubt on the assumption of homogeneity of slope parameters in the panel data analysis. It is well known that cross-section dependence may arise due to common shocks, unobserved common factors, spatial dependence, and idiosyncratic pairwise dependence in the disturbances. The tests of cross-section dependencies are stated as follows. Consider the standard panel data model:

$$y_{it} = \beta' x_{it} + v_{it} \quad i=1, 2, \ldots, N, \; t=1,2,\ldots,T \qquad (1)$$

where y_{it} is the dependent variable and x_{it} is the column vector of regressors for individual *i* at time *t*. v_{it} is the error component that may be cross-sectionally correlated. The latter would imply the following alternative hypothesis is true.

$$\text{Cov}\,(v_{it},\, v_{jt}) \neq 0 \; for\ some\ t\ and\ some\ i \neq j \qquad (2)$$

versus

$$\text{Cov}\,(v_{it},\, v_{jt}) = 0 \; for\ all\ i \neq j$$

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Pesaran (2004) proposes a simple alternative, based on regular product-moment correlation coefficients, which has exactly mean zero for fixed values of either N or T.

$$\mathrm{CD} = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho_{ij}} \xrightarrow{d} N(0,1) \qquad (3)$$

The null hypothesis H_0 is cross-section independence. If the null hypothesis is significantly rejected, we can conclude that the panel data model exhibits substantial cross-sectional dependence in the errors (De Hoyos & Sarafidis, 2006). Cross-section dependence may arise from the increasing economic integration of countries. The fact that strong interdependence between cross-section units leads us to the second generation panel unit root test. On the other hand, if the null hypothesis is not rejected, the assumption of parameter homogeneity across panel members maintains and the first generation of panel unit root will be applied in the next step.

2.2 Panel Unit Root

Because the first-generation panel unit root assumes cross-sectional independence, the presence of cross-section dependence across panel units invalidates the use of first-generation unit root tests in heterogeneous panels. It is particularly true in the context of cross-country (region) regressions. So, we shall use second-generation panel unit root tests that are suitable to overcome the problem of dependence and heterogeneity among cross-section units.[3] The robust version of the Dickey-Fuller t-statistic under contemporaneously correlated errors suggested by Breitung and Das (2005)will be employed to detect the unit root for all of the relevant variables. The relevant equation to evaluate the presence of a unit root is as follows:

$$\Delta y_{it} = \varphi_i y_{i,t-1} + \varepsilon_{it} \text{i=1, 2, .,, N, t=1, 2, …, T} \quad (4)$$

The null hypothesis is (homogeneous nonstationary)

$$H_0; \varphi_i = 0 \text{ for all } i$$

versus the alternatives

$$H_1: \varphi_i < 0 \text{ i} = 1, 2, \ldots,$$

Under the null hypothesis, cross units are I(1) and do not cointegrate. The alternative hypothesis suggested that y_{it} may cointegrate with unobservable common factors. A test of the null hypothesis can be based on the robust t statistics:

[3] Breitung and Das (2005) indicate that cross-sectional independence leads to severe size distortions and low power of the tests.

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$$t_{rob} = \frac{\sum_{t=1}^{T} y_{t-1}^{*} \Delta y_t^{*}}{\sqrt{\sum_{t=1}^{T} y_{t-1}^{*} \hat{\Omega} \Delta y_t^{*}}} \qquad (5)$$

where $\hat{\Omega}$is the covariance matrix. Breitung and Das (2005) showed that t_{rob} has a standard normal limiting null distribution.

Another frequently mentioned by the second generation of panel unit root tests is the factor structure approach, such as Pesaran (2007), Moon and Perron (2004), and Bai and Ng (2004). As indicated by Barbieri (2009), the factor structure approach assumes a common factor representation in which an observed series is written as a linear combination of common and idiosyncratic components. Instead of testing the nonstationarity of y_{it}, Reese and Westerlund (2016) propose a test procedure regarding the unit root and cointegration properties. They combine the cross-section average (CA) augmentation approach of Pesaran (2007), and the principal components-based panel analysis of non-stationarity in idiosyncratic and common components (PANIC) of Bai and Ng (2004) to develop PANICCA, a simple and complete panel unit root toolbox.

2.3 Westerlund (2007) Panel cointegration test

Panel-cointegration techniques are used to study the long-run economic equilibrium relationship among integrated variables, which can be seen in many economic theories such as tests of purchasing power parity, neutrality of money, permanent income hypothesis, and dividend growth model. The first generation of the panel cointegration model usually assumes cross-section independence. Balgati and Pesaran (2007) indicate that it could lead to significant size distortion in the presence of cross-section dependence.

In recognition of the problem of cross-section dependence, the second generation of panel cointegration tests that take account of cross-section dependence in the panel data has been developed. Allowing the possibility for heterogeneity both in the short run and in the long run and dependence across cross-section units, Westerlund (2007) develops the four error correction-based cointegration tests for panel data. The error-based correction equation can be constructed as follows:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i y_{i,t-1} + \lambda_i' x_{i,t-1} + \sum_{j=1}^{P_i} \alpha_{ij} y_{i,t-j} + \sum_{j=-q_i}^{P_i} \gamma_{ij} x_{i,t-j} + \varepsilon_{ij} \qquad (5)$$

The error correction parameter α_i determines the speed at which the system corrects back to the long-run equilibrium relationship. Westerlund argues that $x_{i,t}$and $y_{i,t}$are cointegrated if $\alpha_i < 0$, while $x_{i,t}$and $y_{i,t}$are not cointegrated if $\alpha_i = 0$. The null hypothesis of no cointegration is:

H_0: $\alpha_i = 0$ for all *i*

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The alternative hypothesis consists of four key test statistics. It depends on the assumption of the homogeneity of α_i. The first two tests, called group-mean tests, do not require the α_is to be equal, which means $H_1{:}\,\alpha_i < 0$ for at least one *i*. The other two tests, called panel tests, assume that α_i is equal for all *i* and are designed to test $H_1{:}\,\alpha_i = \alpha < 0$ for all *i.*

2.4 Detecting Structural Breaks

Ditzen and Westerlund (2021) introduce multiple tests for structural breaks in time series and panel data models. The number and period of occurrence of structural breaks can be known and unknown. The model can be expressed in matrix form:

$$Y = X\beta + Z\delta + U(6)$$

where $Y=(y_1, y_2, \dots, y_T)$, $X=(x_1, x_2, \dots, x_T)'$, $\delta=(\delta_1, \delta_2, \dots, \delta_T)'$, and

$$Z = \begin{pmatrix} z_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & z_{s+1} \end{pmatrix}$$

where$Z$ is a $(T_s \times q)$matrix with structural breaks. The break can be unknown or known and single and multiple breaks can occur. In the case of a known breakpoint, The F-Statistic will be employed to test whether the break occurs at a specific point in time. For unknown breaks, they develop three different hypothesizes. The first is no break against the alternative of s breaks; the second hypothesis is no breaks against a lower and upper limit of breaks. The last hypothesis tests the null of s breaks against the alternative of one more break (s+1).

2.5 Estimating Dynamic Common Correlated Effects

Kao & Chiang (2000) indicate that the ordinary least squares (OLS) estimator in the cointegrated regression models in the panel data is asymptotically normal but has a non-zero mean. The authors indicate that FMOLS and DOLS estimators are all normally distributed. As it occurs with first-generation panel unit root tests mentioned above, the key to obtain the asymptotic convergence to the normal distribution of the FMOLS and DOLS estimators was based on the assumption of independence of the cross-section members (countries) of the panel. Eberhardt (2012) suggests that cross-section independence has rarely been seen in the empirical study of macro panels. The Augmented Mean Group (AMG) estimator and the common correlated effects mean group (CCE) estimator are proposed to deal with the problem entailed by the assumption of cross-section independence.

The dynamic correlated effects model, which is similar to AMG estimator was developed by Eberhardt and Teal (2010) can allow for heterogeneous slope coefficients and cross-section dependence on estimation and inference across panel groups (Chudik and Pesaran 2015, Ditzen 2018)). The DCCE estimator includes the cross-section averages of the dependent and independent variables, which can account for the unobserved common factor, as additional regressors. The focus of the estimator is to obtain consistent estimates of the parameters related to the observable variables and is robust to nonstationary common factors. The empirical model for CCE estimator is constructed as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} u_{it} = \gamma_i f_t + \varepsilon_{it} \quad (7)$$

In a dynamic panel setting,

$$y_{it} = \alpha_i + \lambda_i y_{it-1} \quad + \beta_i x_{it} + u_{it} \ \ for\ i = 1, 2, \dots, N\ t = 1, 2, \dots, T \quad (8)$$

where x_{it} is a vector of observable covariates and u_{it}contains the unobservables $f_t$and the error terms ε_{it}. The group fixed effects α_i capture time-invariant heterogeneity across groups and a common factorf_t captures time-variant heterogeneity and cross-section dependence. In equation (8) the lagged dependent variable is no longer strictly exogenous and therefore the estimator becomes inconsistent. Chudik and Pesaran (2015b) show that the estimator gains consistency if $\sqrt[3]{T}$lags of the cross-section means are added.

3. Data, Model, and Results

3.1 Data

To cover as many pandemic periods as possible, container ships' stock returns and global freight return indices have been included in the analysis as of the first case of COVID-19(December 31, 2019, according to World Health Organization).The observations end on July 2, 2021. Weekly data have been taken from Refinitive Financial Datastream and returns have been calculated as the logarithmic change over the previous week. For those of the top ten container ship companies, only six of them are publicly listed: A.P. Moeller-Maersk (OMX Nordic Exchange Copenhagen), Cosco Shipping Holdings Co., Ltd (Shanghai Exchange), Hapag Lloyd AG, (Deutsche Boerse AG Exchange), Evergreen Marine Corp Taiwan Ltd (Taiwan Stock Exchange), Yang Ming Marine Transport Corporation (Taiwan Stock Exchange), and Wan Hai Lines Ltd (Taiwan Stock Exchange). The global freight container shipping indices comprise Freightos Baltic Global PriceIndex, MSCI World Containers and Packaging equity index, Standard and Poor's 500 Containers and Packaging equity index, and MSCI ACWI Containers and Packaging equity index.

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3.2. Model specification

This paper attempts to examine the relationship between container ship stock return and the global freight index during the pandemic period. Before we proceed to the discussion of the results, the econometric model is specified as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \tag{9}$$

where y_{it} is the stock returns of container ship companies in panel setting and x_{it}denotes the global freight container shipping index. The expected sign of all slope coefficients is expected to be positive.

3.3 Results discussions

3.3.1 Cross-section dependence tests

According to Breitung (2015), cross-section dependence among countries or companies becomes a crucial feature because of the feature of financial markets contagion. Breitung also indicates that it cannot just let the intercept vary across companies in the linear regression to represent the heterogeneous pattern.

Based on the discussion of macro panel data, our empirical estimation starts with the tests of cross-sectional dependence (Baltagi & Pesarna, 2007). If the assumption of cross-section independence is satisfied, the first-generation panel unit root tests and first-generation panel techniques will be applied to the sample of container ship companies. We will use the FMOLS and DOLS methodology to estimate the long-run relationship between container ship stock returns and global freight return indices. However, if the assumption of cross-section independence is violated, the second-generation panel units root tests and second-generation panel econometric techniques will be employed to the stationarity of our variables and the long-run relationship among our variables. Given the cointegrating relationship among our empirical model, we will proceed to estimate the relationship between stock returns and equity indices by using the DCCE estimator to take account of the cross-sectional dependence and heterogeneous macro panels.

Since the panel-data models are likely to be subject to the problem of cross-sectional dependence in the errors, we begin to examine the presence of cross-sectional dependence for the sample of stock returns. The empirical examination involves two steps. In step one, we will employ fixed effect (FE) or random effect (RE) estimators in the typical panel-data model. An assumption implicit in estimating this panel-data model is that the cross-sectional units are independent. However, as indicated by De Hoyos & Sarafidis (2006), the FE or RE estimators will be biased and inconsistent if the errors are correlated with included regressors. Step two executes the three testing procedures of cross-section dependence (CD test)-named Friedman's (1937) test

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statistic, the statistic proposed by Frees (1995), and the cross-sectional dependence (CD) test of Pesaran)2004). Pesaran shows that the CD test statistics, under the null hypothesis of no cross-sectional dependence, are distributed as the mean of zero and standard deviation of 1.

The obtained results from the cross-sectional dependence test are summarized in Table 1. Table 1 presents four different kinds of modeling settings and three different testing procedures. The explanatory variables in Model (1)-Model (4) are Freightos Baltic Global Price Index, MSCI ACWI Containers and Packaging equity index, MSCI World Containers and Packaging equity index, and Standard and Poor's 500 containers and Packaging equity index, respectively. As we would have expected from the highly significant results of the CD test, both Frees' and Friedman's tests reject the null of cross-sectional independence. The results of the three cross dependence tests indicate that container ships' stock returns and global freight container indices are highly dependent across indices. The existence of cross-section dependence in the errors provides evidence that the second generation of panel econometric technique is appropriate to proceed for our sample.

Table 1. Tests of Cross Section Dependence

	Model (1)	Model (2)	Model (3)	Model (4)
	test statistics	test statistics	test statistics	test statistics
Friedman's test of cross sectional independence	231.6***	209.0***	201.5***	214.9***
Frees' test of e cross-sectionally independent	1.062***	0.869***	0.881***	0.911***
Pesaran's test of cross-sectionally independent	12.64***	11.68***	11.77***	11.98***

Note: The null hypothesis is cross section independence. *,**,*** denote the significance level at 10%, 5%, and 1%, respectively. Friedman test for cross-sectional dependence using Friedman's chi-square distributed statistic. Frees test for cross-sectional dependence using Frees' Q distribution (t-asymptotically distributed).

The explanatory variable in Model (1) is Freightos Baltic Global Price Index. The explanatory variable in Model (2) is MSCI ACWI Containers and Packaging equity index. The explanatory variable in Model (3) is MSCI World Containers and Packaging equity index. The explanatory variable in Model (4) is Standard and Poor's 500 Containers and Packaging equity index.

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Table 2 Panel Unit Root Test

Panel A: Breitung (2005) Panel Unit Root Test

Varaible	Level	First Difference
stock price	1.515	-10.18***
Freightos Baltic Global Price Index	6.249	-3.368***
MSCI ACWI Containers and Packaging equity index	-1.169	-9.862***
MSCI World Containers and Packaging equity index	-0.173	-9.899***
Standard and Poor's 500 Containers and Packaging equity index	-0.213	-10.22***

Panel B: Reese and Westerlund (2016) Panel Unit Root Test

	Common Factors		Idiosyncratic components		
explanaotry variable	MQ_c	MQ_f	P_a	P_b	*PMSB*
Freightos Baltic Global Price Index	-60.14***	-9.379***	-62.52***	-10.96***	-1.634**
MSCI ACWI Containers and Packaging equity index	-67.66***	-10.35***	-63.64***	-10.50***	-1.447*
MSCI World Containers and Packaging equity index	-67.31***	-9.922***	-65.24***	-10.66***	-1.463*
Standard and Poor's 500 Containers and Packaging equity index	-66.46***	-11.85***	-65.19***	-10.65***	-1.462*

Note: The null hypothesis is that there exists unit root. *,**,*** denote the significance level at 10%, 5%, and 1%, respectively.

3.3.2 Panel unit root tests

Breitung (2005) proposes a robust version of the OLS t-statistic for testing unit roots in a macro panel subject to cross-section dependence in unobserved components. Results of Breitung's unit root test are reported in Table 2 of panel A. The second-generation panel unit root test cannot reject the null hypothesis of a unit-root process at a level for container ship stock price, Freightos Baltic Global Price Index. MSCI ACWI Containers and Packaging equity index, MSCI World Containers and Packaging equity index, and standard and Poor's 500 Containers and Packaging equity index. When differencing the above variables, the null hypothesis of nonstationary is strongly rejected at the 1% significant level. This implies that the order of integration for all the variables is found to be *I (1)*.

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Panel B of Table 2 presents the results of PANICCA estimation. Rather than employing principal component (PA) methodology, the use of the cross-section average (CA) augmentation approach by Reese and Westerlund (2016) leads to the superior performance of small-sample performance over Bai and Ng (2004), especially in the type of small- to medium-N panels. The resulting combined approach of CA and PANIC leads to the same asymptotic theory as the PANIC approach. Panel B shows that the null hypothesis of a unit root is rejected at a 10% significance level for the common factors component while the statistically significant results of idiosyncratic components show stationarity for four different kinds of explanatory variables.

3.3.3 Westerlund (2007) Panel cointegration test

As indicated by Granger (1986), if a pair of series x_t, y_t both are $I(1)$ and there exists a constant A, such that $z_t = x_t - Ay_t$ is $I(0)$, then x_t, $y_t$will be said to be cointegrated. Based on the discussion above, variables integrated in the same order, i.e. $I(1)$, facilitate examining long-run equilibrium relationships using panel cointegration techniques. The panel cointegration framework that allows for cross-section dependence, nonstationary and parameter heterogeneity has been deployed for this purpose.

The evidence of cross-section dependence invalidates the use of the first generation panel cointegration model to estimate the long-run relationship between the stock returns and container freight index. The error-correction-based cointegration tests developed by Westerlund (2007), which allow for dependence both within and between the cross-sectional units, will be employed to examine the stock return-freight index relationship. Westerlund proposes four key test statistics, two of which are referred to as panel statistics (P_α, P_t) and the other two statistics are referred to as group mean statistics ((G_α, G_t). For group mean statistics, the null hypothesis indicates no cointegration for cross-sectional unit *i* while the alternate hypothesis suggests that at least one of the cross-sectional units is cointegrated. By contrast, for the panel statistics, a rejection of the null hypothesis should be taken as evidence of cointegration for the panel as a whole

Table 3 reports the results of Westerlund (2007) panel cointegration tests for the stock return-freight index relationship during the COVID-19 pandemic period. Table 3 not only provides the panel statistics and group mean statistics but also shows bootstrapped p-values for all four test statistics. The results of the four models show that group mean test statistics G_t is significant at 1 % level, which means that the null hypothesis of no cointegration can be rejected; suggesting that at least one of the cross-sectional units is cointegrated. Furthermore, the panel test statistics $P_\alpha$and P_t are statistically significant at 1 % level. The rejection of the null hypothesis is considered as evidence of cointegration for the panel as a whole. Interestingly, the robust p-value of

Table 3 Westerlund (2007) Panel cointegration test

	Model (1)			Model (2)			Model (3)			Model (4)		
	Test Statistics	*P-value*	*Robust P-value*	*Test Statistics*	*P-value*	*Robust P-value*	*Test Statistics*	*P-value*	*Robust P-value*	*Test Statistics*	*P-value*	*Robust P-value*
Group-mean tests												
G_t	-6.042***	0.000	0.000	-6.432***	0.000	0.000	-6.424***	0.000	0.000	-6.374***	0.000	0.000
G_a	-52.84***	0.000	0.000	-54.92***	0.000	0.000	-56.76***	0.000	0.000	-56.58***	0.000	0.000
Panel tests												
P_t	-14.64***	0.000	0.000	-14.98***	0.000	0.000	-14.96***	0.000	0.000	-14.85***	0.000	0.000
P_a	-51.26***	0.000	0.000	-53.06***	0.000	0.000	-52.97***	0.000	0.000	-52.80***	0.000	0.000

Note: The null hypothesis is no cointegration. The alternative hypothesis is all panels are cointegrated. *,**,*** denote the significance level at 10%, 5%, and 1%, respectively.
The explanatory variable in Model (1) is Freightos Baltic Global Price Index. The explanatory variable in Model (2) is MSCI ACWI Containers and Packaging equity index. The explanatory variable in Model (3) is MSCI World Containers and Packaging equity index. The explanatory variable in Model (4) is Standard and Poor's 500 Containers and Packaging equity index.

P_t from the bootstrap approach is also statistically significant at the 1% level for both panel and group mean statistics.[4] The bootstrap test results provide

Table 4 Detection of Structural Breaks

Panel A: Test for multiple breaks at unknown breakdates
H_0: no break(s) vs. H_1: 1 <= s <= 2 break(s)

	Test Statistic	*1% Critical Value*	*5% Critical Value*	*10% Critical Value*
UDmax(tau)	8.96***	6.09	4.74	4.13

Estimated break points: w45 w57

Panel B: Test for multiple breaks at unknown breakdates
H_0: 1 vs. H_1: 2 break(s)

	Test Statistic	*1% Critical Value*	*5% Critical Value*	*10% Critical Value*
*F(s+1|s)**	-5.37	19.77	15.72	13.91

* s = 1

Panel C: Test for multiple breaks at known breakdates
H_0: no break vs. H_1: 1 break

	Test Statistic	*1% Critical Value*	*5% Critical Value*	*10% Critical Value*
supW(tau)	8.34***	6.09	4.66	4.03

Estimated break points: w57

Note: *,**,*** denote the significance level at 10%, 5%, and 1%, respectively.

strong evidence for the failure to reject the alternative of cointegration. Thus, the overall evidence from the Westerlund (2007) tests for cointegration indicate that

[4] The bootstrap tests are implemented using 100 bootstrap replications.

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there is a long-run relationship between container ships' stock returns and global container freight indices.

3.3.4 *Detecting Structural Breaks*

Given the evidence of panel cointegration, the long-run relations of the analyzed variables can be further estimated. Because Coronavirus disease has led to an unprecedented global destructive slump in the stock market. It is reasonable to detect the structural change of the stock market before estimating the long-run relationship between stock returns and global container freight indices. By definition, structural break refers to the structural change in the deterministic components of time series over periods. In this paper, we consider the methodology of Ditzenet al. (2021) because it allows testing for many known or unknown structural breaks in a heterogeneity panel with an error factor structure. The testing procedure proposed by Ditzen et al. (2021) implements three hypotheses: Hypothesis 1 is no break against the alternative of *s* breaks, hypothesis 2 is no breaks against a lower and upper limit of breaks, hypothesis 3 tests the null of *s* breaks against the alternative of one more break (*s+1*).

Table 5 Estimating Dynamic Common Correlated Effects with Breaks

Varaible	Model (1)		Model (2)		Model (3)		Model (4)	
	coefficient	*P-value*	*coefficient*	*P-value*	*coefficient*	*P-value*	*coefficient*	*P-value*
Freightos Baltic Global Price Index	0.370***	0.002						
MSCI ACWI Containers and Packaging equity index			0.514***	0.000				
MSCI World Containers and Packaging equity index					0.497***	0.000		
Standard and Poor's 500 Containers and Packaging equity index							0.462***	0.000
D1988	5.100***	0.001	5.186***	0.001	5.196***	0.000	5.188***	0.001
Root Mean Squared Error (sigma)	9.34		9.13		9.15		9.18	
CD Statistics	11.87***	0.000	10.66***	0.000	10.77***	0.000	11.02***	0.000

Note: *,**,*** indicate significance at 10%, 5%, and 1%, respectively.

The dummy variable D_{1988} is equal to 1 if year is greater than 1987 and is equal to zero, otherwise.

Table 4 contains three panels of the detection of structural breaks during the COVID-19 pandemic period. Asymptotic critical values depending on the number of breaks and regressors are given in Bai and Perron (1998, Table 1). The identification of structural breaks involves three steps. We first test multiple breaks at unknown breakdates by testing for no break vs. up to 2 breaks. Panel A indicates that the test statistics are statistically significant at 1% level. The strong evidence of rejection of the null hypothesis also suggests that there are two breaks at weeks 45 (11/13/2020) and weeks 58 (2/12/2021). Once the one or two breaks are confirmed, hypothesis 3 will be further employed to test for H_0: 1 vs. H_1: 2 break(s). The insignificant test statistics in panel B favor the null hypothesis of 1 break. The final step in panel C tests for multiple breaks at known breakdates. The rejection of the hypothesis of no break implies that one break is found during the pandemic period. Thus, the structural break is identified at weeks 58 (2/12/2021) in our sample.

Chinese New Year officially began on February 12, 2021. As a result of COVID-19, Chinese governments imposed internal travel restrictions and kept factories open to offset a disruption to all production. However, most truckers chose to go home for Lunar New Year-made them subject to 14 days' quarantine after travel and unable to deliver goods between factories and ports. The breakdown in intermodal connectivity, longer production, and inventory backlogging could delay shipment and worsen global supply chains.

3.3.5 Estimating Dynamic Common Correlated Effects with Breaks

Having established the presence of long-run equilibrium relations and structural break, the next step would estimate the long-run equilibrium relationship among analyzed variables by the Dynamic Common Correlated Effects (DCCE) estimation procedure (Chudik and Pesaran, 2015).The DCCE extends the Common Correlated Effects (CCE) approach developed by Pesaran (2006) to heterogeneous panel data models with lagged dependent variables and/or weakly exogenous regressors. Ditzen (2018) introduces an estimation procedure for DCCE, the mean group, and the pooled mean group estimator. The cross-sectional dependence Test (CD Test) is automatically calculated. Under the null hypothesis, the error terms are weakly cross-sectional dependent.

The long-run estimation results estimated based on the DCCE estimator are given in Table 5.Chudik and Pesaran (2015) argued that the DCCE method is robust to cross-section dependence with lagged dependent variables and/or weakly exogenous regressors. In Table 5, the CD statistics of four different explanatory variables are all statistically significantly different from zero.[5] Thus, the hypothesis of weak cross-sectional dependence can be rejected after applying DCCE tests. One of The significant benefits of the DCCE approach is that it is a very robust estimator in the presence of structural breaks (Kapetanios et al. 2011). The inclusion of dummy variable D_{1988}in Table 5attempts to capture the structural change caused by novel Coronavirus disease. The coefficient onD_{1988} in column (1) is 5.1. This significantly positive coefficient implies that the stock return in container shipping companies after Chinese New Year, on average, earns 5.1 % more than the days before 2021/02/12, given the Freightos Baltic Global Price Index. The coefficients on D_{1988} in columns (2) -(4) also exhibit economic significance and statistically positive significance. The existence of structural break was supported by the fact of spot freight rates at record level before the 2021 Chinese New Year. They were significantly higher on the Shanghai-Rotterdam,

[5] The number of the cross-section means set to 3.

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Shanghai-Genoa, and Shanghai-Los Angeles trades compared to the 2020 Chinese New Year.

Turning to the impact of freight index on container ship stock returns, columns (1) -(4) of Table 5 show the estimated results of four different global freight indices on container ships' stock returns. Freightos Baltic Global Price Index is found to have a positive coefficient value of 0.37 in the long run with significance at 1%. It means that a 1% increase in the Freightos Baltic Global Price Index can increase the container ships' stock returns by 0.37% in the long run. Similarly, the coefficient of MSCI ACWI Containers and Packaging equity index is 0.514 indicating a 1% rise in MSCI ACWI Containers and Packaging equity index would lead to an upsurge in stock returns by 0.514%. A 1% rise in MSCI World Containers and Packaging equity index and Standard and Poor's 500 Containers and Packaging equity index raise the container ship stock returns by 0.497 % and 0.462% correspondingly. All the coefficients on the freight index variables are positive and statistically significant at 1% level. The findings are consistent with the findings presented by Mazur et al. (2021). On the other hand, it seems that the MSCI ACWI Containers and Packaging equity index has the greatest impact on the container ships' stock returns than the other freight equity indices in terms of economic significance.

Generally, results base on the DCCE estimates shows that there are robust long-run relations between analyzed variables. The findings are aligning with UNCTAD (2021) and International Transport Forum (2020). At the start of the COVID-19 pandemic, containerized trade experienced a downturn. Approximately 20 to 30% of the container ship capacity on the main trade lanes was idled between February and June 2020 (International Transport Forum, 2020). However, lockdown and pandemic led to the changes in consumption and shipping patterns, including the huge demand in electronic commerce and the increased import demand for manufactured consumer goods.

A shortage of containers and container ships resulted in the container crisis. The container crisis is exacerbated by port labor shortages, port congestions, and capacity constraints in trucks. When the Ever Given container ship blocked traffic in the Suez Canal for 6 days in March, container spot freight rates have surged more than 10%. As of the second half of 2021, strengthening of vaccination coverage and varying speeds of recovery worldwide, as well as stimulus packages supporting consumer demand and persistent supply-chain bottlenecks have contributed to leading to a further increase in containerized trade flows and a new surge in container spot freight rates. As a result, the top main container carriers made large profits in 2021

From the above discussion, we draw three critical points. First, the global container freight indices play a pivotal role in the stock returns of container shipping companies. DCCE estimated results indicate that the long-run relationship between

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stock returns and freight indices supports the notion of the long-short strategy of investment in the stock market. Second, the empirical outcomes confirm the presence of cross-sectional dependence across global container freight indices. This implies that the first-generation panel estimation methodology will yield biased and inconsistent estimators. It is better to apply the second generation panel econometric technique to explore the container ship stock return-freight indices relations during the COVID-19 pandemic period. Third, we test for known or unknown structural breaks without COVID-19 variables and investigate the linkage between those breaks and COVID-19, thus providing explicit empirical evidence about whether Coronavirus disease affects container ship stock returns.

4. Conclusion

The Coronavirus pandemic 2019 has killed 616,493 people in the U.S. as of August 7th, 2021, with corresponding COVID-19 cases of 616,493. This has created significant turmoil not only in the global economic activity but also in the stock market. This study investigates the dynamic responses of stock returns of container shipping companies to the global container freight indices. Notably, stock return responses are positively related to structural break and global freight indices in the COVID-19. The structural break is attributed to the 2021 Chinese New Year, strong demand, a shortage of containers, saturated ports, and too few ships and dock workers. Carriers posted a record EBIT result of $27.1 billion in the first quarter of 2021, up from $1.6 billion during the same period last year. In this study, we show that, during the COVID-19 pandemic, stocks in the container shipping sector perform abnormally well and generate extraordinary returns. We also show that the long-run relationship between container ships' stock return and global container freight indices may signal the opportunity to implement the log-short strategy in container ship stock during the COVID-19 pandemic period. The DCCE long-run estimated results imply that the MSCI ACWI Containers and Packaging equity index contributes most than other global container freight indices in tracking the container stocks.

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