International Economics 172 (2022) 29–39

Contents lists available at ScienceDirect

International Economics

journal homepage: www.elsevier.com/locate/inteco

Bunker fuel, commodity prices and shipping market indices following the COVID-19 pandemic. A time-frequency analysis☆

Manuel Monge

Universidad Francisco de Vitoria, Faculty of Law, Business and Government, E-28223, Madrid, Spain

A R T I C L E I N F O

JEL classification:
Q41
N70
R40
R41

Keywords:
Bunker fuel
Commodity prices
Shipping market indices
Transportation congestion
COVID-19
Fractional integration
FCVAR model
Wavelets

A B S T R A C T

This paper deals with the analysis of the evolution of international trade after COVID-19, examining commodity prices, the shipping industry, and the influence of the cost of bunker fuel. To this end, we use techniques based on fractional integration, fractional cointegration VAR (FCVAR) and wavelet analysis. Monthly data relating to heavy fuel oil prices and the shipping market from October 2011 to September 2021 are used. Using fractional integration in the post-break period, a lack of mean reversion is observed in all cases, which means that, for the commodity prices and shipping market indices, a change in trend will be permanent after COVID-19 unless strong measures are carried out by the authorities. Using wavelet analysis, we conclude that the demand shock represented in the indices mentioned above has led the price of fuel oil since the beginning of the pandemic, and bunker fuel is not relevant in determining the cost of maritime transport.

1. Introduction

In December 2019, the pandemic experienced around the world provoked by COVID-19 has had a severe and versatile impact on society and consequently on the economy (Sohrabi et al., 2020). To reduce the incidence of this virus, governments around the world imposed a series of restrictions including, among others, distancing rules, the temporary closure of trade and service companies, catering, hotel business, and leisure facilities, mobility restrictions for non-essential trips and the obligation to wear a mouth-and-nose cover.

Financial markets (Ramelli and Wagner, 2020) and national economies (Atkeson, 2020) have been affected by this virus that first appeared in Wuhan, in the city of Hubei (Sohrabi et al., 2020). Furthermore, the labor market (see Yu et al., 2020; Monge, 2021) and certain sectors in particular have been affected by the restrictions such as, among others, the health sector (see Mishra and Rampal, 2020; Okoi and Bwawa, 2020), the energy sector (see Fezzi and Fanghella, 2020; Gil-Alana and Monge, 2021), and the tourism sector (see de Vos, 2020; Wang et al., 2020).

Baqaee and Farhi (2020), through a disaggregated model that includes multiple sectors, multiple factors, input-output linkages, downward nominal wage rigidities, credit-constraints and zero lower bound, try to measure the impacts of the COVID-19 on the relationship between supply and demand.

According to Ludvigson et al. (2020) and from the demand point of view, people have been accumulating supplies as a response to

☆ Manuel Monge acknowledge support from an Internal Project of the Universidad Francisco de Vitoria..

E-mail address: manuel.monge@ufv.es.

https://doi.org/10.1016/j.inteco.2022.08.003
Received 21 March 2022; Received in revised form 12 July 2022; Accepted 20 August 2022
Available online 26 August 2022

shortages as the epidemic has spread. Also, we have witnessed how our purchasing habits have changed, increasing the demand for delivery services and online shopping through the internet, considerably increasing the volume of freight transport and the demand for supplies (see Liu, T. et al., 2020; Liu, M et al., 2020).

On the supply side, due to the closure of factories and stoppages in production, the supply chain has been affected globally. Araz et al. (2020) state that the pandemic outbreak has brought about the most serious disruption encountered in decades, interrupting many global supply chains. Fortune (2020) revealed that 94% of the Fortune 1000 companies reported disruptions, driven by coronavirus, in their supply chains. Furthermore, in a report issued by Dun and Bradstreet (2020), 51,000 companies around the world are listed as having one or more direct suppliers in Wuhan and at least 5 million companies around the world have one or more tier-two suppliers in the Wuhan region, the origin of COVID-19. Moreover, 938 of the Fortune 1000 companies have tier-one or tier-two suppliers in the Wuhan region. Finally, Linton and Vakil (2020) conclude that the world's largest 1000 supply chains own more than 12,000 facilities in the quarantine areas.

Following Ivanov (2020), the SARS-CoV-2 outbreak corresponds to a special case of supply chain risks (within the concept disruption risks mentioned in the papers of Ivanov et al., 2017; Kinra et al., 2020; Hosseini et al., 2019) because it scales up quickly and disperses over many geographic regions, similar to SARS, MERS, Ebola, Swine flu, etc. This kind of risk is characterized by three components: first, long-term disruption and its unpredictable scaling. Second, simultaneous disruption in the supply chain (i.e., the ripple effect) and epidemic outbreak propagation in the population (i.e., pandemic propagation), and finally, simultaneous disruptions in the infrastructure of supply, demand, and logistics.

The chief link in the global supply chain is represented by the shipping industry which accounts for 80% of the total transport that takes place globally (UNCTAD, 2019).

Dittmann and Granger, 2002 argue that the international economic and trade environment affect the shipping market, this being a periodic market based on international trade.

Many research papers conclude that there is high volatility in the maritime transport market (see Veenstra and Franses, 1997; Kavussanos and Alizadeh, 2001; Alizadeh and Nomikos, 2011; Alizadeh, 2013; Dai et al., 2014; Tsouknidis, 2016; Theodossiou et al., 2020; Bai and Lam, 2021; among others).

There are several research papers that try to identify the influential factors on freight rates (see Beenstock and Vergottis, 1989; Xu et al., 2011; Dai et al., 2015; Bai and Lam, 2019; Gavriilidis et al., 2018; Angelopoulos et al., 2020; Lim et al., 2019; Alizadeh and Talley, 2011; Adland et al., 2016). Although, the freight rate is largely determined by supply and demand fundamentals, these two variables do not fully explain the high volatility experienced in the shipping market. According to Papapostolou et al. (2014, 2016) market sentiments can be part of the market fundamentals discrepancy. On the other hand, Grammenos and Arkoulis (2002) stated that the shipping industry is affected by oil prices, laid up tonnage and exchange rates. Angelopoulos et al. (2020) confirmed the lead and lag relationship between oil prices and freight rates in shipping markets, therefore enabling better forecasting for the tanker and the dry bulk market (Gavriilidis et al., 2018; Michail, 2020).

Therefore, the objective of this paper is to understand the evolution of international trade after COVID-19 through the analysis of commodity prices, the shipping industry and the influence of the cost of bunker fuel oil prices. To this end, we carry out a statistical analysis using an ARFIMA model (fractional integration techniques) to understand the statistical properties of the time series. Moreover, to understand the long-term relationship of the time series we use a Fractional Cointegration VAR (FCVAR) approach. Finally, we do a wavelet analysis to analyze the structural change produced by the COVID-19 outbreak.

In the maritime economic literature, we find evidence of mean reversion (see Zannetos, 1966; Strandenes, 1984; Tvedt, 1997; Adland and Cullinane, 2006; among others) and unit root behavior (non-stationary) in the spot freight rate (see Berg-Andreassen, 1996; Glen and Rogers, 1997; and Kavussanos and Alizadeh, 2002; among others). There are three reasons behind this behavior: first, the high degree of persistence in spot freight rate series (see Adland and Cullinane, 2006). Second, the choice of testing method, usually the Augmented Dickey-Fuller (ADF) unit root test (Dickey and Fuller, 1979; Said and Dickey, 1984). Adland and Cullinane (2006) show mean reversion in the extremes of the spot freight rate distribution. Finally, and according to Koekebakker et al. (2006), even if the assumption of non-stationary freight rates does not hold in a strict sense, it may be a convenient one from a technical point-of-view.

To the best of our knowledge, this is the first paper that has analyzed the statistical properties of shipping indices and bunker fuel using the methodologies mentioned above. Therefore, the key objectives of our study are twofold. First, we want to carry out a univariate analysis to understand the behavior of each time series. Second, our intention is to examine whether the impact of heavy fuel oil prices on the shipping indices and commodity prices is temporary or permanent. This knowledge is extremely relevant to analyze what the effects of fuel oil prices on may be on shipping and commodity indices. The study is both crucial and timely as, despite the importance of oil in the literature in economics, political science and international relations, there is surprisingly little scholarly discussion regarding the role bunker fuel oil plays in shipping markets.

The structure of this paper is as follows. Section 2 describes the data and the methodology applied in the research paper. Section 3 shows the principal findings. Section 4 presents the conclusions.

2. Data and methodology

2.1. Dataset

To carry out this research paper, we have obtained our dataset from Thomson Reuters Eikon. The variables that we use are: the Bloomberg Commodity Index representing the prices of raw materials, the Baltic Dry Index (BDI) representing the average cost per ton of chartering a vessel to transport raw materials, such as metals, grain and fossil fuel, by sea on the 26 routes around the world, the

HARPEX Shipping Index is slightly different to the BDI because this is an indicator of global economic fleet shipping activity that tracks changes in freight rates for container ships over broad categories. In addition, we consider the Shanghai Containerized Freight Index that shows the most up-to-date freight prices for container transport from the Chinese main ports, including Shanghai. Finally, we use prices of the bunker fuel that is used aboard vessels and which affects time-charter and spot rates, dry bulk and container ship indexes. We use monthly data from October 2011 to September 2021. The time series defined previously are represented in Fig. 1.

Taking into account the new desulphurization legislation (Zis and Cullinane, 2020), the substitution effect between shipping segments (Kavussanos and Visvikis, 2016) and different vessel sizes (Tsouknidis, 2016), we can observe in Fig. 1 that the shipping markets were still recovering when the new virus hit the markets, at which point freight rates dropped by 73% for the dry bulk segment, 36% for the dirty tankers segment and 30% for the clean tanker segment (see Michail and Melas, 2020). In contrast, so far this year, the price of raw materials measured through the Bloomberg Commodity Index has increased by 33% and has reached highs not seen since 2015. Also, the Baltic Dry Index that measures daily the average cost per ton at which ship owners charter their vessels and through which 95% of the global transport of solid raw materials is carried out, has accumulated an increase of almost 250%. Container shipping as measured by the Harpex index has appreciated 800% since June last year. Another way to measure this is through the prices paid for containers between the main routes in the world using the Shanghai Shipping Exchange Containerized Freight Index, which includes the 15 largest global routes with the port of Shanghai. This index, which averages all the journeys made, has accumulated an increase of 65% so far this year.

2.2. Unit roots

To analyze the stationarity of our dataset we have employed unit root tests such as ADF tests based on Fuller (1976) and Dickey and Fuller (1979). Non-parametric estimates of spectral density of u_t at zero frequency have been used following the methodology proposed by Phillips (1987) and Phillips and Perron (1988). Finally, the stationary test of Kwiatkowski et al. (1992) and the unit root tests proposed by Elliot et al. (1996) and Ng and Perron (2001) have been used, taking into account their deterministic trends. We conclude that the same results have been produced by all of them.

2.3. ARFIMA (p, d, q) model

The non-stationary nature of many economic and financial time series is an important characteristic that can be described by several models. The standard approach until the 1980s was to use deterministic functions of time where the residuals on the regression model were I(0) stationary. Following the research carried out by Nelson and Plosser (1982) there was a consensus that the non-stationary component of most series was stochastic and the use of unit roots or first differences I (1) was the way to go. On the other hand, to achieve stationarity I (0), the number of differences does not necessarily have to be an integer value, since it can be any point on the real line and therefore fractional I(d).

Observations that are far apart in time but highly correlated is a feature of long memory and is able to be captured by the I(d) models. The form of this models is:

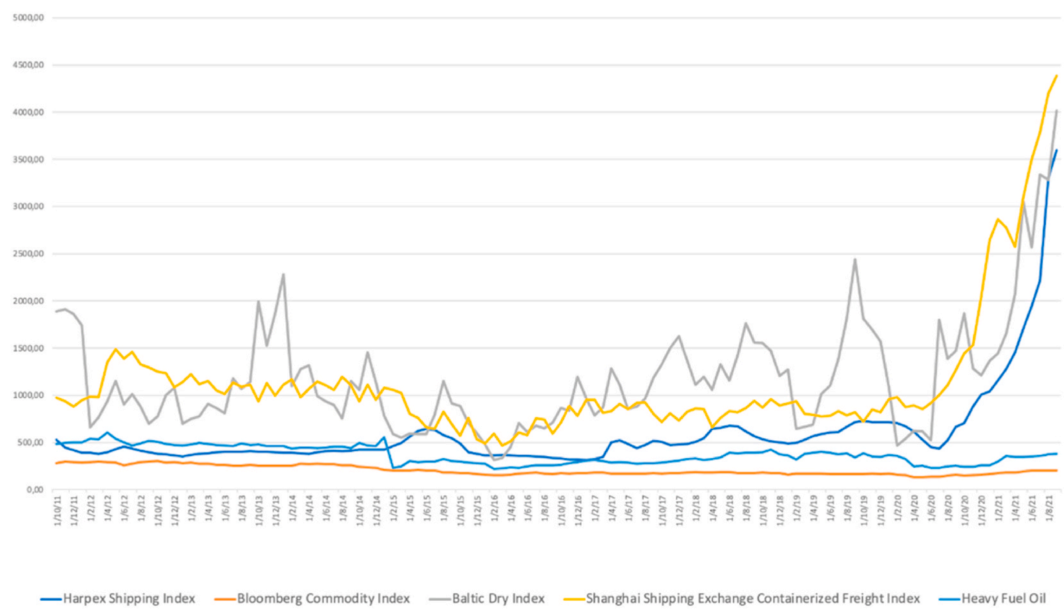

Fig. 1. Behavior of prices of freight, commodities and heavy fuel oil prices.

$$(1-L)^d x_t = u_t, \quad t = 1,\ 2,\ \ldots, \tag{1}$$

where x_t represents a time series, d represents any real value, L is the lag-operator $(Lx_t = x_{t-1})$ and the covariance stationary process is represented by u_t where the spectral density function, which is positive and finite at the zero frequency, displays a type of time dependence in the weak form. For this reason, we can state if u_t is ARMA (p, q), x_t is ARFIMA (p, d, q). Adenstedt (1974), Granger and Joyeux (1980), Granger (1980, 1981) and Hosking (1981) were the authors who introduced the idea of fractional integration.

From equation (1), the polynomial $(1-L)^d$ is expressed in terms of binomial expansion where for all real d, x_t depends not only on a finite number of past observations but on its entire history. Thus, a higher value of d implies a higher level of association between the observations of the series.

Given the parameterization in (1), one can distinguish between several cases depending on the value of the parameter d, and several specifications based on (1) can be observed. Following Hosking (1981), Table 1 below summarizes the different values of d and the corresponding consequences for the mean (or trend), variance, and duration of the shock.

We present our results following the likelihood process suggested by Sowell (1992) in contrast to various other procedures (see Geweke and Porter-Hudak, 1983; Phillips, 1999, 2007; Robinson, 1994, 1995a,b; etc.). Following the Akaike information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC) (Akaike, 1979) we select the most appropriate ARFIMA model.

2.4. FCVAR model

The Fractionally Cointegrated Vector AutoRegressive (FCVAR) model is a generalization of Johansen's (1996) Cointegrated Vector AutoRegressive (CVAR) model to allow for fractional processes of order d that co-integrate to order $d-b$ with $b>0$. The FCVAR model was introduced by Johansen (2008) and developed by Johansen and Nielsen (2010, 2012). The advantage of this model is that it allows the use of stationary and non-stationary time series.

To introduce the FCVAR model, we present first the non-fractional CVAR model. Being Y_t, $t = 1, \ldots, T$ a p-dimensional I(1) time series, the CVAR model is:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t. \tag{2}$$

where Δ^b and $L_b = 1 - \Delta^b$ represent the difference and the lag operator. These are used to derive the FCVAR model. We then obtain:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L_b^i Y_t + \varepsilon_t, \tag{3}$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \tag{4}$$

where, ε_t is p-dimensional independent and identically distributed with mean zero, and variance-covariance matrix Ω. The parameters α and β are $p \times r$ matrices, where $0 \le r \le p$. In matrix β the columns are the cointegrating relationships and $\beta' X_t$ are the stationary combination, i.e., the long-run equilibrium, which is integrated to order d, and the short-term parts from the long-run equilibrium are integrated to order $d-b$. The coefficients in α correspond to the speed of adjustment unto equilibrium. Therefore, $\alpha\beta'$ is the adjustment long-run and Γ_i represents the short-run behavior of the variables.

In contrast to the CVAR model, there are two additional parameters in the FCVAR model. The order of fractional integration of the observable time series is represented by the parameter d. The degree of fractional cointegration, that is, the reduction in fractional integration order of $\beta' X_t$ compared to X_t itself, is represented by the parameter b.

The relevant ranges for b are $\left(0, \frac{1}{2}\right)$, in which case the equilibrium errors are fractional of order greater than $1/2$ and therefore non-

Table 1
Interpretation of the results of ***d*** for the ARFIMA models.

d	Mean (or trend) and variance	Shock duration
$d = 0$	Short-run mean-reversion Finite variance	Short-lived
$0 < d < 0.5$	Long-run mean reversion Finite variance	Long-lived
$0.5 \le d < 1$	Long-run mean reversion Infinite variance	Long-lived
$d = 1$	No mean-reversion Infinite variance	Infinite
$d > 1$	No mean-reversion Infinite variance	Infinite; effect increase as time moves forward

stationary although mean-reverting, and $\left(\frac{1}{2}, 1\right]$, in which case the equilibrium errors are fractional of the order less than 1/ 2 and are stationary (Dolatabadi et al., 2015). Note that for $d = b = 1$, the FCVAR models is reduced to the CVAR model, which is thus nested in the FCVAR model as a special case.

As an intermediate step towards the final model, we consider a version of model (2) with d = b as an assumption of no persistence in the cointegration vectors and a constant mean term for the cointegration relations. That is to say:

$$\Delta^d X_t = \alpha(\beta' L_d X_t + \rho') + \sum_{i=1}^{k} \Gamma_i \Delta^d L_d{}^i X_t + \varepsilon_t \tag{5}$$

The simple model considered is the following:

$$\Delta^d (X_t - \mu) = L_d \alpha \beta' (X_t - \mu) + \sum_{i=1}^{k} \Gamma_i \Delta^d L_d{}^i X_t + \varepsilon_t \tag{6}$$

where μ represents the level parameter that shifts each of the series by a constant to avoid the bias related to the starting values in the sample (Johansen and Nielsen, 2014). $\beta' \mu = -\rho'$ represents the mean stationary cointegrating relations.

The asymptotic analysis in Johansen and Nielsen (2012) shows that the maximum likelihood estimators of $(d, \alpha, \Gamma, \ldots, \Gamma_2)$ are asymptotically normal, while the maximum likelihood estimator of (β, ρ) is asymptotically mixed normal when $d_0 < 1/2$ and asymptotically normal when $d_0 > 1/2$. Several empirical papers such as Baruník and Dvořáková (2015); Maciel (2017); Aye et al. (2017); Dolatabadi et al. (2018); Jones et al. (2014); Gil-Alana and Carcel (2020); Monge and Gil-Alana (2021); Monge and Cristóbal, 2021; among others have used FCVAR models.

The MATLAB codes for the FCVAR model estimation are provided in Nielsen and Popiel (2018).

2.5. Continuous Wavelet Transform (CWT)

Continuous Wavelet Transform (CWT) has been applied to several research papers in finance and economics in order to understand the behavior of time series in the time-frequency domain (see Aguiar-Conraria and Soares, 2011 and 2014; Vacha and Barunik, 2012; Dewandaru et al., 2016; Tiwari et al., 2016; Jammazi et al., 2017; Monge and Gil-Alana, 2021; Monge and Cristóbal, 2021; among others).

Stationarity is not required to carry out a wavelet analysis. This methodology also allows us to find evidence of changes in patterns between the time series being analyzed.

Two tools are used with this methodology to get the results: wavelet coherency and wavelet phase-difference.

First, we use wavelet coherency that shows the correlation in time and frequency between both time series in a dimensional diagram in a function of τ and a, identifying hidden patterns or information. The $WT_x(a, \tau)$ is defined as:

$$WT_x(a, \tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-\tau}{a}\right) dt,$$

where $WT_x(a, \tau)$ refers to wavelet coefficients of $x(t)$; a refers to the position of a wavelet in the frequency domain, τ refers to the position in the time domain. The mother wavelet (ψ) that has been chosen for this research paper has been Morlet because we are able to measure the synchronism between time series due to its characteristics of complex sine wave within a Gaussian envelope (see Aguiar-Conraria and Soares, 2014).

Second, we use the wavelet coherence to interpret and understand the integration of the time series obtained in the previous step. Thus, we define the wavelet coherence as:

$$WCO_{xy} = \frac{SO\left(WT_x(a, \tau) WT_y(a, \tau)^*\right)}{\sqrt{SO\left(|WT_x(a, \tau)|^2\right) SO\left(|WT_y(a, \tau)|^2\right)}},$$

where SO is a smoothing operator in both time and scale. Without the smoothing operator, the wavelet coherency would be always one for all times and scales (see Aguiar-Conraria et al., 2008 for details). Aguiar-Conraria's website provides the CWT's MATLAB code for the calculations of estimators and test statistics..[1]

3. Empirical results

3.1. Unit roots tests

To examine the statistical properties of the original series and its differences to obtain robust results, we start the analysis by

[1] https://sites.google.com/site/aguiarconraria/joanasoares-wavelets.

performing the Augmented Dickey-Fuller test (ADF), Phillips and Perrron (Phillips and Perron, 1988) and Kwiatkowski et al.,1992. Table 2 displays the results, which suggest that.

3.2. results of long memory tests

According to the methodology explained before, and the low power of the unit root methods under fractional alternatives,[2] we use ARFIMA (p, d, q) models to study the persistence of (…). AIC criterion (Akaike, 1973) and BIC (Akaike, 1979) criterion were selected to select AR and MA orders in the models[3]

The estimates of d following the maximum likelihood estimator proposed by Sowell (1992) are in Table 3. We have considered various ARFIMA (p, d, q) specifications with all combinations of $p,\ q \leq 2$ for each time series.

The first thing that we observe from Table 3 is that Heavy Fuel Oil, the Bloomberg Commodity Index and the Baltic Dry Index show evidence of mean reversion ($d < 1$) with estimated values of d equal to 0.79, 0.96 and 0.53, respectively. However, if we follow the confidence interval for these time series, in the case of commodity prices and the Baltic Dry Index the unit root null hypothesis $I(1)$ cannot be rejected, while for the remaining two series (the Harpex Shipping Index and the Shanghai Shipping Exchange Containerized Freight Index), this hypothesis is rejected in favor of a higher degree of integration. With the exception of Bunker fuel, there is no evidence of mean reversion in any single case and the shocks are expected to be permanent (e.g., lasting forever), causing a change in trend. Therefore strong measures will be required by the authorities to recover the original trends.

3.3. results of FCVAR

To contrast the possible existence of persistence in the long-run co-movements of the series, we use FCVAR model proposed by Johansen and Nielsen (2012). Table 4 summarizes the results of the FCVAR model.

Following the indications suggested by Jones et al. (2014) regarding the lag value ($k = 3$). Also, we consider deterministic components and cointegration rank (r) to get our results. In the upper part of Table 4, we report the results assuming that $d = b$, i.e., that the long run equilibrium relationship is I(0). Evidence of cointegration is found in all cases with the lowest degree of integration observed in the case of commodity prices (0.642). If the coefficients for d and b are supposed to be different, some evidence of a low order of cointegration is found in the case of the prices for container transport from the Chinese main ports ($d = 0.810$ and $b = 0.645$). For the rest of the cases, d is equal to b ($d = b$) supporting the standard cointegration, i.e., I(0) behavior in the equilibrium errors. Considering the results of the cointegrating test for Bunker fuel and Shanghai Shipping Exchange Containerized Freight Index under the assumption of $d \neq b$, we cannot reject the hypothesis where the shock duration is mean-reverting in the long-run. In all other cases, we assume that the shock duration has a short-lived duration due to the short-run stationary behavior.

3.4. COVID-19 and Continuous Wavelet Transform

To identify the dependence over time and to study the behavior of the structural change caused by COVID-19, we have calculated the wavelet coherency and phase difference between Bunker fuel and the remaining indices. The results are displayed in Fig. 2.

Panel (a) represents the wavelet coherency that explains the interrelations between both time series, showing the strength of the relationship and in which frequency occurs. From scale 1 (a single month) up to scale 16 (approximately one year and four months), the frequencies are displayed on the vertical axis. All the sample period is represented in the horizontal axis.

To identify the high frequency and the high coherence with statistical significance of local correlations between the time-frequency domain we have used Monte Carlo simulations, where the regions with significance values at 5% are represented by the black contour. The relation of both time series, one in relation to the other, is understandable using the frequency bands represented in panel (b) and (c), that are the 1–12 frequency band and the 12.5–16 frequency band, respectively.

Focusing on the start of the pandemic outbreak in China, in December 2019 we observe from Fig. 2 statistically significant coherency in the four results obtained. Doing the analysis by indexes, the first result is related to the bunker prices and commodity prices. We observe in the pandemic outbreak a high degree of coherence in the low frequency (short-term) that corresponds to cycles between 3 and 12 months. Second and third results are related to the bunker fuel prices and the Baltic Dry Index and bunker fuel prices with the Harpex index, respectively. The interrelations between these two pairs of time-series occur in the short-term, between 3 and 4 months. Finally, we have calculated the coherency between heavy fuel oil prices and the Shanghai Shipping Exchange Index obtaining the same result as the previous ones.

If we focus on the phase-difference, we observe that the high coherency mentioned before for the pandemic episode stay between 0 and $-\pi/2$, which means that heavy fuel oil prices are negatively correlated with every index mentioned before. Thus, the demand shock represented in the indices mentioned in this paper have led the price of fuel oil since the beginning of the pandemic, and bunker fuel is not relevant to determining the cost of maritime transport.

Once we have reached this result and knowing that it is the demand shock that is guiding the behavior of the price of maritime transport fuel, we analyze statistically the behavior of this demand through the different indices already mentioned previously. To do

[2] See Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).

[3] According to Hosking (1981) and Beran et al. (1998), the AIC and BIC criteria could not be the best criteria under the assumptions of fractional models.

Table 2
Unit roots tests.

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Heavy Fuel Oil	−0.8343	−2.0764	−2.1451	−2.1482	−2.4979	1.2537	0.3581
Bloomberg Commodity Index	−1.4365	−1.8956	−0.5724	−1.6114	−0.6586	1.9261	0.4327
Baltic Dry Index	0.1824	−0.9468	−1.7042	−1.6693	−2.3136	0.6054	0.2326
Harpex Shipping Index	3.6221	6.5247	6.0029	10.361	8.843	1.0023	0.2711
Shanghai Shipping Exchange Containerized Freight Index	3.1728	3.5613	3.1298	4.6202	4.1646	0.5635	0.3592

(i) Refers to the model with no deterministic components.
(ii) with an intercept, and.
(iii) with a linear time trend.
* Denotes a statistical significance at the 5% level.

Table 3
Results of long memory tests.

Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
Long memory test						
Heavy Fuel Oil	120	ARFIMA (2, d, 2)	0.79	0.1050238	[0.62, 0.96]	I(d)
Bloomberg Commodity Index	120	ARFIMA (2, d, 2)	0.96	0.1186170	[0.76, 1.16]	I(1)
Baltic Dry Index	120	ARFIMA (2, d, 1)	0.53	0.283567	[-0.11, 1.17]	I(0), I(1)
Harpex Shipping Index	120	ARFIMA (1, d, 1)	1.47	0.0441022	[1.40, 1.54]	I(d > 1)
Shanghai Shipping Exchange Containerized Freight Index	120	ARFIMA (2, d, 2)	1.42	0.1203744	[1.22, 1.62]	I(d > 1)

Table 4
Results of the FCVAR model.

Series	$d = b$	β	α	μ
Bloomberg Commodity Index	0.642	$Var\,1 = 1.000$	$Var\,1 = -0.171$	$Var\,1 = 493.566$
	(0.102)	$Var\,2 = -1.236$	$Var\,2 = 0.001$	$Var\,2 = 281.787$
Baltic Dry Index	0.721	$Var\,1 = 1.000$	$Var\,1 = -0.014$	$Var\,1 = 505.931$
	(0.142)	$Var\,2 = -1.092$	$Var\,2 = 0.083$	$Var\,2 = 1715.034$
Harpex Shipping Index	0.875	$Var\,1 = 1.000$	$Var\,1 = 0.000$	$Var\,1 = 486.312$
	(0.107)	$Var\,2 = -11.570$	$Var\,2 = -0.018$	$Var\,2 = 472.299$
Shanghai Shipping Exchange Containerized Freight Index	0.828	$Var\,1 = 1.000$	$Var\,1 = 0.007$	$Var\,1 = 475.284$
	(0.181)	$Var\,2 = -0.427$	$Var\,2 = -0.401$	$Var\,2 = 1034.456$
Series	$d \neq b$	β	α	μ
Bloomberg Commodity Index	$d = 1.104$ (0.155)	$Var\,1 = 1.000$	$Var\,1 = -0.217$	$Var\,1 = 481.800$
	$b = 1.104$ (0.280)	$Var\,2 = -1.510$	$Var\,2 = -0.024$	$Var\,2 = 282.478$
Baltic Dry Index	$d = 0.112$ (0.000)	$Var\,1 = 1.000$	$Var\,1 = -2.527$	$Var\,1 = 512.503$
	$b = 0.112$ (0.000)	$Var\,2 = -0.806$	$Var\,2 = -34.288$	$Var\,2 = 1722.663$
Harpex Shipping Index	$d = 0.875$ (0.136)	$Var\,1 = 1.000$	$Var\,1 = 0.000$	$Var\,1 = 486.312$
	$b = 0.875$ (0.232)	$Var\,2 = -11.570$	$Var\,2 = -0.018$	$Var\,2 = 472.299$
Shanghai Shipping Exchange Containerized Freight Index	$d = 0.810$ (0.207)	$Var\,1 = 1.000$	$Var\,1 = 0.032$	$Var\,1 = 476.524$
	$b = 0.645$ (0.599)	$Var\,2 = -0.406$	$Var\,2 = -0.789$	$Var\,2 = 1017.848$

so, we use ARFIMA models. The results are reported in Table 5.

We observe from Table 5 that the estimates of d after structural change are below 1 only for the Baltic Dry Index. Nevertheless, focusing on the confidence interval, we see that the Baltic Dry Index and the remaining time series cannot reject the hypothesis I(1). Thus, we cannot reject the hypothesis of I(1) in any case, implying a lack of mean reversion and that shocks are expected to be permanent, causing a change in trend.

4. Concluding comments

This paper contributes to the literature on understanding the behavior of commodity prices and the shipping market under the influence of heavy fuel oil prices after a pandemic outbreak such as COVID-19.

The increase in the demand for delivery services and online shopping through the internet occasioned by the changes in our purchasing habits during the pandemic (see Liu et al., 2020a; Liu et al., 2020b) and the closure of factories and stoppage in production, have meant that the supply chain has been affected globally (see Araz et al., 2020). A bottleneck has been generated in international trade affecting a shipping industry which accounts for 80% of the total transportations that are taking place globally (UNCTAD, 2019).

Furthermore, oil price is a key factor for the shipping industry as oil is the main energy source for the transport of commodities by

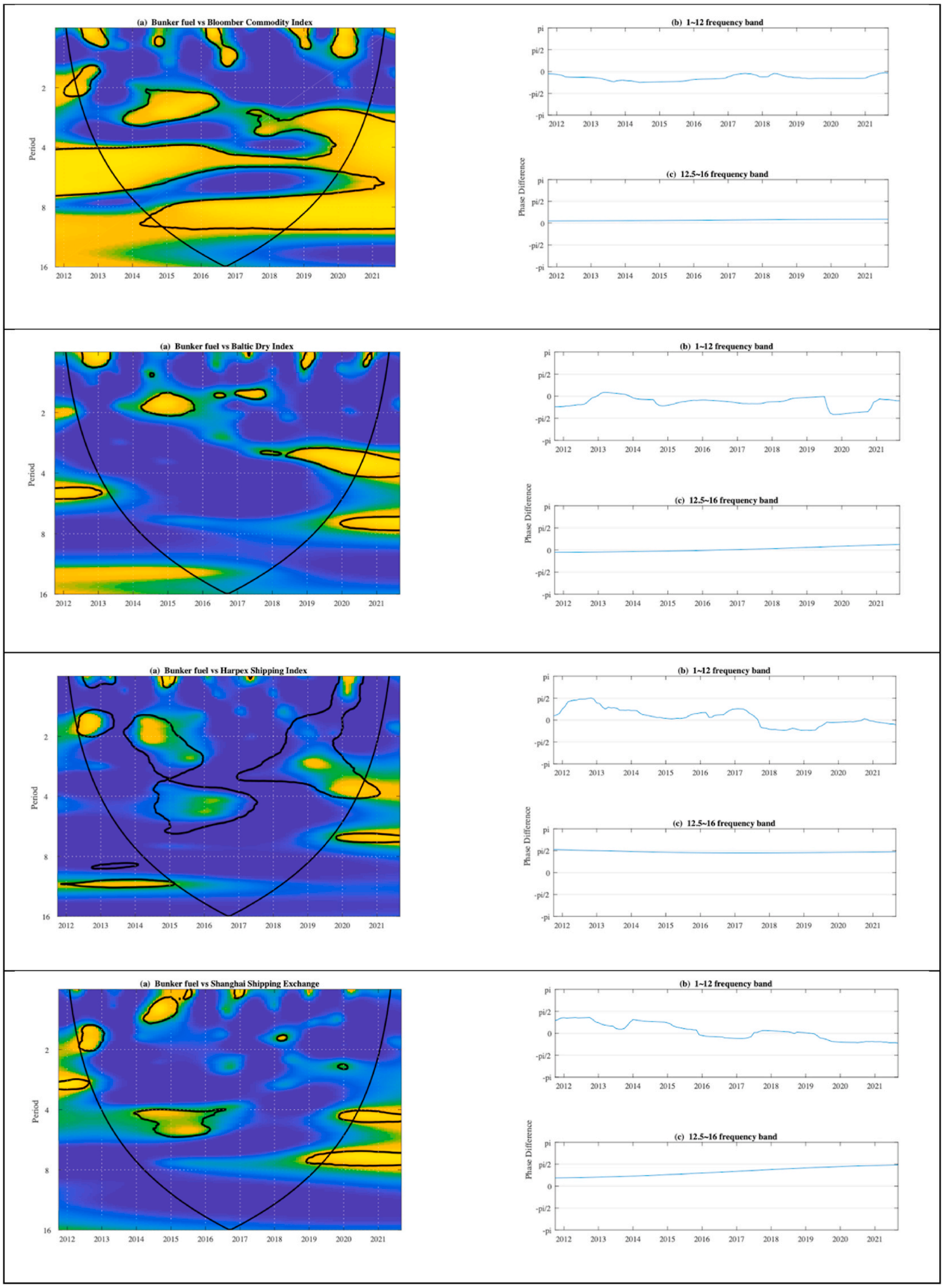

Fig. 2. Wavelet coherency and phase difference results.
The contour designates the 5% significance level. Coherency ranges from blue (low coherency) to yellow (high coherency). (a) Wavelet coherency. (b)-(c)Phase difference. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

sea throughout the world, and shipping markets play a role in final prices of energy, agricultural goods and metals (Geman and Smith, 2012).

To carry out our analysis we use bunker fuel to represent oil prices, Bloomberg the Commodity Index represents commodity prices and finally, the Baltic Dry Index, the HARPEX Shipping Index and The Shanghai Containerized Freight Index represent the shipping

Table 5
Results of long memory tests after COVID-19 break.

Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
Long memory test						
Bloomberg Commodity Index	22	ARFIMA (0, d, 0)	1.09	0.1841467	[0.79, 1.39]	I(1)
Baltic Dry Index	22	ARFIMA (0, d, 0)	0.77	0.238872	[0.38, 1.16]	I(1)
Harpex Shipping Index	22	ARFIMA (0, d, 0)	1.32	0.142127	[1.09, 1.55]	I(d > 1)
Shanghai Shipping Exchange Containerized Freight Index	22	ARFIMA (0, d, 0)	1.22	0.1203744	[0.91, 1.53]	I(1)

industry. Monthly data from October 2011 to September 2021 are used.

We analyze the statistical properties of these time series, measuring the degree of persistence by using fractional integration techniques. Moreover, we analyze the long-term relationship of the time series using a Fractional Cointegration VAR (FCVAR) approach. The results show that heavy Fuel Oil, Bloomberg Commodity Index and Baltic Dry Index show evidence of mean reversion ($d < 1$) with a estimated values of d equal to 0.79, 0.96 and 0.53, respectively. But, if we follow the confidence interval for these time series, in the case of commodity prices and the Baltic Dry Index the unit root null hypothesis $I(1)$ cannot be rejected, while for the remaining two series (the Harpex Shipping Index and the Shanghai Shipping Exchange Containerized Freight Index), this hypothesis is rejected in favor of a higher degree of integration. Except for the Bunker fuel, there is no evidence of mean reversion in any single case and the shocks are expected to be permanent (e.g., lasting forever), causing a change in trend. Thus, strong measures will be required by the authorities to recover the original trends.

Considering the results of cointegrating test that analyze the long-run behavior of heavy fuel oil with respect to the other variables we conclude that for Bunker fuel and the Shanghai Shipping Exchange Containerized Freight Index under the assumption of $d \neq b$, we cannot reject the hypothesis where the shock duration is mean-reverting in the long-run. In all other cases, we assume that the shock duration has a short-lived duration due to the short-run stationary behavior.

In addition, to identify the dependence over time and to study the behavior of the structural change occasioned by COVID-19, we calculate the wavelet coherency and phase difference. We conclude that the demand shock represented in the indices mentioned in this paper has led the price of fuel oil since the beginning of the pandemic, and that bunker fuel is not relevant to determining the cost of maritime transport.

The findings are of great interest to analyze what the effects of bunker fuel are on commodity prices and the shipping industry, helping market participants to understand better what it is happening in international trade.

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