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Testing for nonlinearity and chaos in liquid bulk shipping

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Abstract

Modelling and forecasting port traffic are of major importance for the shipping industry. Existence of chaos implies that while long term forecasting is vain, reliable short-term forecasting would be possible. The objective of this research is to uncover the nonlinear dynamics and chaotic behavior of the liquid bulk cargo shipping, using monthly data from January 1992 to March 2013 for the Spanish seaports. For this purpose, in first instance we remove any linear dependence by means of the Box-Jenkins approach. Afterwards we analyzed the existence of nonlinearity and chaotic behavior by applying the BDS and the Lyapunov test respectively. Our findings suggest that although there has been found a dominant nonlinear structure underlying the dynamics of the liquid bulk traffic, determinism cannot be assumed and hence chaos cannot be inferred. These results are especially relevant for modeling and forecasting of maritime traffic, specifically for liquid bulk cargo, and for the design and evaluation of public policies related to the investment planning and management of port system.

Keywords: Shipping; Liquid bulk; Time series; Chaos; Nonlinear dynamics; Forecasting.

1. Introduction

According to International Maritime Organization (IMO), maritime transport emerges as a relevant key player in the world's economy, as over 90% of all the world's trade is carried by sea and it is the most cost-effective way to move masse goods and raw materials around the world. The tanker market is generally concerned with the transportation of crude oil and petroleum products which are mainly used to manufacture other goods (UNCTAD, 2012). In 2012 the tanker sector represents around one third of the international seaborne trade by volume and 22 per cent per value (UNCTAD, 2012). In Spain, in 2013 it also accounted around of 33% of total shipping of goods.

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In the last decades the interest in nonlinear models, and in particular in chaotic behavior defined as nonlinear deterministic processes that look random, has increased dramatically. A main feature of chaotic system in order to forecasting consists of its sensitive dependence on initial conditions (Brock et al., 1991). The major advantage of detecting chaos in the underlying process of a time series is that while long term forecasting is vain, reliable short term forecasting is possible (Brooks, 1998). In fact, when considering other types of transport, forecasts based on chaos theory have been shown to have greater predictive power than other methods (Frazier and Kockelman, 2004).

Research on modelling maritime transport has traditionally assumed linear models but only a few studies have explored the nonlinear and chaos dynamics. Regarding the behavior and forecasting of shipping freight rates and container traffic, Goulielmos and Psifia (2007), Goulielmos and Psifia (2009), Thalassinos et al. (2009), Goulielmos and Kaselimim (2011) and Goulielmos et al. (2012) unveil the existence of nonlinearity and chaos. However, this research on chaos involves techniques derived from other sciences (e.g. physics) that do not account for the specific characteristics of financial time series like noise and the limited and low sample size. Thus, their findings might be biased (McKenzie 2001; BenSaïda and Litimi, 2013 and Su et al, 2014).

Specifically, for the case of Spanish seaports, Inglada-Perez (2010) studies five different shipping series including liquid bulk, and in all the cases a nonlinear pattern was rejected. Thus, a chaotic behavior was rejected. Yet, the existence of chaos in demand for liquid cargo shipping rates remains as an open and relevant issue. Its importance lies in the fact that finding low-dimensional chaos would allow short-term reliable forecasting.

To the best of our knowledge, our study is at the moment the only one in which the chaotic behavior dynamic of the underlying process of the liquid bulk shipping has been considered. Our main contribution is that unlike previous studies herein we take into account those years that correspond to the global economic worldwide crisis (January 1992-March 2013) and that when testing for chaos we consider modern techniques that can deal with noisy time series.

In order to determine whether the monthly series of liquid bulk cargo exhibits a nonlinear stochastic or deterministic chaotic behavior for the period, we apply the following methodology. First all linear dependencies are removed from the data by applying autoregressive integrated moving average (ARIMA) filters based on the Box-Jenkins methodology (Box and Jenkins 1970). Next, we use BDS procedure to detect the existence of nonlinearity. If nonlinear dependence is detected, then it might be caused by the existence of a volatility cluster. This being the case, the appropriate generalized autoregressive conditional heteroskedasticity (GARCH) and exponential GARCH models (EGARCH) (Nelson, 1991) are applied. Afterwards, the existence of chaotic motion is explored by means of Lyapunov exponent procedure that is ideally suitable for noisy time series analysis, (BenSaïda and Litimi, 2013). Our findings suggest although there is a high evidence of nonlinearity, the series seems to have a stochastic rather than a deterministic nature.

This study contributes to filling the gap in the existing international literature on the nonlinear and chaotic behavior of demand for liquid shipping. Its incremental contribution against related literature in modelling and forecasting of freight rates consists of being the first study that applies methods and techniques the that can address noise. Moreover, the novelty lies on the fact that to the best of our knowledge, this study constitutes the first time in which these techniques have been applied to that variable. The empirical findings obtained from analytical results suggest that nonlinearity is present in the underlying process of the liquid shipping traffic, although, we did not find any clear evidence of chaos.

The remainder of the paper is organized as follows. In Section 2 we provide a description of the most relevant milestones of the employed methodology. In Section 3 we describe the database data used and investigate the univariate time series properties of the data for the period January 1992–March 2013. In Section 4 we describe the results obtained, discussing the evidence in favour of and against the existence nonlinearity and chaos. Section 5 summarizes some conclusions.

2. Methodology

The methodological framework applied consists of several stages. The following are the most significant milestones of the methodology. Details can be checked elsewhere (Inglada-Pérez, 2016)First, all linear dependencies are removed from the data by applying autoregressive integrated moving average (ARIMA) filters based on the Box-Jenkins methodology (Box and Jenkins 1970). Next, we use BDS procedure to detect the existence of nonlinearity. If nonlinear dependence is detected, then it might be caused by the existence of a volatility cluster. This being the case, the appropriate generalized autoregressive conditional heteroskedasticity (GARCH) and exponential GARCH models (EGARCH) are applied. Afterwards, the existence of chaotic motion is explored by means of Lyapunov exponent procedure that is ideally suitable for noisy time series analysis (BenSaïda and Litimi, 2013).

The non-parametric BDS test (Broock, et al., 1997) analyzes the existence of dependence in a time series. The null hypothesis is that the series is independent and identically distributed (i.i.d.) against the alternative hypothesis that the data is not i.i.d. It is capable of detecting a variety of possible deviations from independence and has been shown to have high power in detecting various types of nonlinearity.

Lyapunov exponent:

Lyapunov exponents determine the sensitivity to initial conditions, a property of chaotic systems. They determine the rate of separation of nearby trajectories whose initial conditions only differ by a small infinitesimal difference. A positive largest Lyapunov exponent implies sensitive dependence, and therefore that we have evidence of chaos (Brook, 1998). In this research, we followed the algorithm proposed by Bensaida and Litimi (2013). Briefly it consists in the following steps:

Consider a time series $\{x_t\}_{t=1}^{T}$ represented as:

$$x_t = f(x_{t-L}, x_{t-2L}, \ldots, x_{t-ML}) + \varepsilon_t \tag{1}$$

Where *L, m, ε* and *f* stand for the time delay, the embedding dimension, noise added to the series and an unknown chaotic map, respectively. The exponent (LE) is defined as

$$\hat{\lambda} = \frac{1}{2M} \ln(v_1) \tag{2}$$

where *M* stands for an arbitrarily selected number of observations and is v_1 the largest eigenvalue of the matrix $(T_M U_0)'(T_M U_0)$ with, $T_M = \prod_{t=1}^{M-1} J_{M-T}$ and J_t the Jacobean matrix.

Because f is usually unknown, it is needed to approximate the Jacobean matrix. The authors employ a single-layer feed-forward neural network using nonlinear least squares for different values of $m = 1,..,8$ and later calculate the *LE* spectrum. Hence, the chaotic system is estimated by the following equation:

$$x_t \approx \alpha_0 + \sum_{j=1}^{q} \alpha_j \tanh(\beta_{0,j} + \sum_{i=1}^{m} \beta_{i,j} X_{t,iL}) + \varepsilon_t \tag{3}$$

(*L, m q*) are selected as the triplet that provides the highest value for λ, and are associated with the complexity of the system. The test for chaos is then constructed based on the asymptotic distribution of λ (Shintani and Linton, 2004).

3. Data

We use monthly Spanish shipping sea transport service series on liquid bulk cargo, from 1992:1 to 2013:3 (255 observations). The data is available online at http://www.fomento.es/. Summary statistics of the main series are presented in Table 1. Fig.1 shows the monthly temporal evolution. It is observed that the series maintains a general trend of growth throughout the period. Within this pattern, it is found a significant decrement that corresponds to the global economic crisis (i.e. the year 2008).

Table1. Descriptive statistics

	Original Series	Difference series	ARMA(2,1)MA(1)$_{12}$	GARCH(1,0)	EGARCH(0,1)
Mean	1114xE4	0.0002	-0.0045	-0.0467	-0.0471
Std. Dv.	1366xE4	0.0990	0.0613	0.8596	1.0042
Median	1120xE4	0.0033	-0.0037	-0.1045	-0.0820
Minimum	803xE4	-0.2565	-0.1550	-2.0781	-2.5581
Maximum	1451xE4	0.3024	0.1645	2.4882	2.2030
Skewness	0.0934	0.0683	0.2556	0.4340	0.2246
Kurtosis	2.2548	2.9582	2.9070	3.1920	2.6520
Jarque Bera	6.2703*	0.2057	2.6992*	7.9017*	3.2291
N	255	242	240	240	240

Notes: Statistics for the time series considered in this study; original series, difference series, and residuals of ARMA, GARCH, and EGARCH models**.** Skewness and Kurtosis Coefficient correspond to the Fisher asymmetry coefficient and the kurtosis coefficient, respectively. * The asterisk reflects that the result is significant at the 95% confidence level.
Source: Own elaboration.

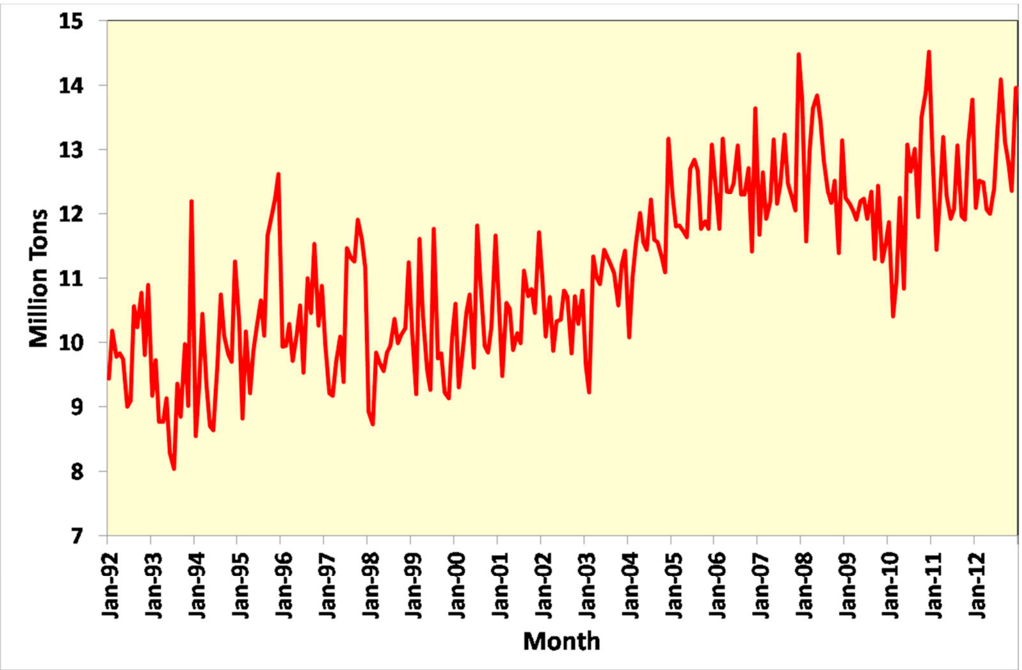

Fig.1 Evolution of the Liquid Bulk Cargo.
Jan stands for January.

4. Empirical Results

4.1. Linear Modeling

In the first instance we eliminate the trend and seasonal cycle from the original series and obtain a new stationary series. Hence, in this first stage, we transform the original series by taking logarithms and a seasonal and a regular difference (from now on referred as difference series).

The difference series appears to be stationary without the existence of any trend (fig.2). In order to verify that the time series adheres to the stationarity hypothesis, we performed several procedures (MacKinnon, 1996). We examine the stationary property by the Augmented Dickey-Fuller test (Dickey and Fuller, 1979), the Phillips-Perron test (Philips and Perron, 1988) and the Kwiatkowski-Phillips-Schmidt-Shin stationary contrast (Kwiatkowski et al., 1992) for both a constant term and a constant and a trend. According to their results, the series is stationary and the original series is defined as I(1) (see Table 2).

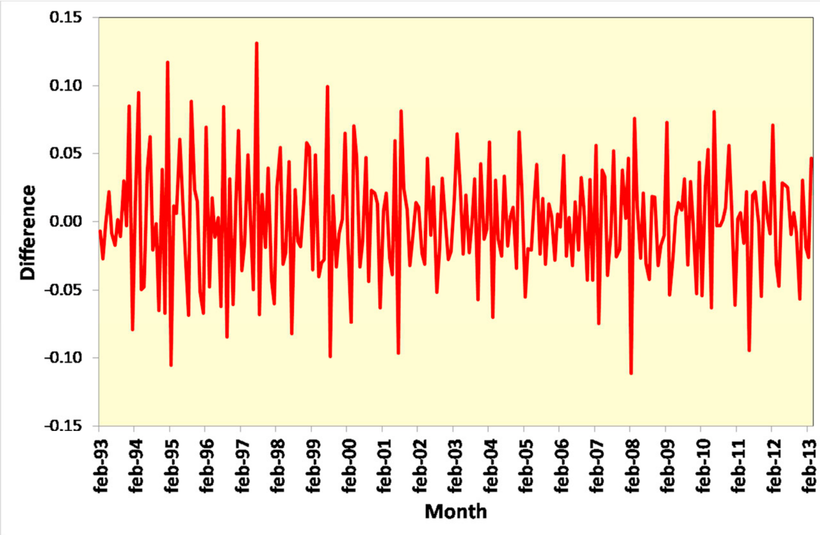

Fig.2 Evolution of the Difference Series.
Feb stands for February month.

Next, we filter the difference series with a linear ARMA model (Box and Jenkins 1970, 1975), According to the algorithm described by Barkoulas et al. (2012), the best model corresponds to the ARMA(2,1)MA(1)$_{12}$. The residuals obtained constitute the input of the following steps of the methodological process. The principal statistics for the residuals are displayed in Table 1 (ARMA(2,1)MA(1)$_{12}$ series). The latter residuals, present means values close to zero, are negative skewed and leptokurtic and they do not seem to follow a normal distribution (Jarque-Bera statistic $\leq$ 0,005).

Table 2. Stationarity analysis

	Original Series	Difference Series
Augmented Dickey-FullerTest (ADF)		
Constant	-0.641 (0.857)	**-6.888 (0.000)**
Constant and Trend	**-10.6489 (0.0000)**	**-6.885 (0.000)**
Phillips-Perron Test (PP)		
Constant	**-6.405 (0.000)**	**-46.469 (0.000)**
Constant and Trend	**-11.459 (0.000)**	**-46.566 (0.000)**
Kwiatkowski-Phillips-Schmidt-Shin Test (KPSS)		
Constant	1.923	**0.046**

Constant and Trend	0.161	**0.043**

Notes: Augmented Dickey-Fuller p-values correspond to one-sided p-values. For the Phillips-Perron test, lags were based on the bandwidth Newey-West using Bartlett kernel. Critical values for the Kwiatkowski-Phillips-Schmidt -Shin test are 0.463 and 0.146 respectively for the constant and linear plus linear tendency model. Significant values at the 95% confidence level are in bold.

Subsequently, we checked for the presence of a nonlinear component in the residuals of the SARIMA model, through the application of the BDS test. Likewise, the BDS test is used following the methodology suggested by Brock et al. (1996). Once all linear dependence has been removed from the data, this test becomes an indirect mechanism for analyzing the existence of nonlinear dependence (Barnet et al., 1997).

Results in Table 3 support the existence remaining dependence in the data as the BDS test strongly rejected the null i.i.d. hypothesis in all but one case. Thus, some kind of dependence, such as nonlinearity, must remain in the data.

Table 3. BDS results

Epsilon/M	**0.5*σ**	**1*σ**	**1.5*σ**	**2*σ**
ARMA(2,1)MA(1)$_{12}$				
2	0.0042	**0.0110**	**0.0119**	**0.0093**
	0.0609	**0.0470**	**0.0239**	**0.0147**
3	**0.0041**	**0.0195**	**0.0280**	**0.0240**
	0.0115	**0.0051**	**0.0019**	**0.0012**
4	**0.0018**	**0.0203**	**0.0364**	**0.0360**
	0.0372	**0.0028**	**0.0016**	**0.0008**
5	0.0003	**0.0151**	**0.0359**	**0.0411**
	0.4406	**0.0097**	**0.0055**	**0.0027**
GARCH(1,0)				
2	-0.0016	-0.0036	-0.0010	-0.0002
	0.5203	0.5070	0.8529	0.9515
3	0.0012	0.0003	0.0067	0.0030
	0.5043	0.9626	0.4696	0.6961
4	0.0007	0.0030	0.0132	0.0045
	0.4652	0.6703	0.2588	0.6807
5	-0.0001	3E-05	0.0102	2.2E-05
	0.9029	0.9959	0.4290	0.9987
EGARCH(0,1)				
2	-0.0007	0.0014	0.0002	0.0011
	0.6343	0.7257	0.9709	0.7384
3	0.0008	0.0026	0.0008	0.0020
	0.4111	0.5945	0.9219	0.7577
4	0.0004	0.0044	0.0062	0.0073
	0.4384	0.3287	0.4980	0.4094
5	3.3E-05	0.0033	0.0063	0.0083
	0.8777	0.3591	0.5220	0.4533

The first line corresponds to the statistic value and the second one to the associated p-value. Significant values are in bold. M corresponds to the embedding dimension.

4.2. Volatility clustering

Nonlinearity, seasonality patterns and cluster volatility are some of the characteristics that can be founded in the shipping markets (Abouarghoub, 2013). Herein, we have empirically verified the existence of a nonlinear component. Next we analyze if it is originated from the presence of conditional volatility (heteroskedasticity). We applied ARCH(q) family models. Interestingly these models have been previously applied to other transport series (Guo et al., 2008). We considered the best GARCH and EGARCH models (Bollerslev, 1986) to address the heteroscedasticity present in the data.

EGARCH models in contrast with GARCH models estimate the conditional variance considering the sign of the innovation in the previous period taking into account that volatility can react asymmetrically to good news and bad news. They successfully capture asymmetric response in the conditional variance and hence they are suitable candidates to model financial processes. According to the criteria described above, we fitted both GARCH(1,0) and EGARCH(0,1) models. Then the residuals were standardized, as previously described (Barkoulas et al. 2012). The standardized residuals of all the series, are less leptokurtic (with an average value of 4) that those from the ARMA models (Table 1).

To compare both models and decide which reflects best the temporal variation of the variance, we used the following criteria: (i) lowest residual sum of squares: (ii) lowest Schwarz criterion (Schwarz, 1978); and (iii) greater value of the log-likelihood function. As shown in Table 4, the best model according to all the criteria, is the EGARCH(0,1) model.

Table 4 Model Comparison Criterion

Criterion	GARCH(1,0)	EGARCH(0,1)
Sum squared residuals	1.030039	0.908340
Schwarz criterion	-2.409744	-2.618035
Log-likelihood	308.3515	336.0868

4.3. Chaos Analysis

The existence of nonlinearity is important, since it is a necessary, but not a sufficient condition for chaos. We tested nonlinearity presence by means of the BDS results on the standardized residuals of the GARCH and EGARCH models. No significant results were found at a 5% of the level of confidence suggesting that there is no clear evidence of nonlinearity in neither of the models. Thus, it does not seem to be any evidence of a chaotic component.

Testing for Chaos: Lyapunov Test

In this research we have employed the algorithm described by Benshaida and Litimi (2013) and Wolf et al, (1985) because this method, unlike the most common method, is capable of addressing the noise, that is frequently present in economic time series. The results are shown in Table 5. As expected, we obtained negative significant Lyapunov exponents in all cases. Therefore, no chaotic component evidence is reported.

Table 5. Lyapunov Test Results

Series	(L,m,q)	Lambda	P-value	Hypothesis
Difference Series	(2,6,5)	-0.0930	4.98E-07	H_1
ARMA(2,1)MA(1)$_{12}$	(5,6,5)	-0.2952	2.98E-11	H_1
GARCH (1,0)	(4,6,4)	-0.1532	0.0281	H_1
EGARCH(0,1)	(3,4,4)	-0.0022	0.5082	NA

The null hypothesis of chaos is rejected when the p-value is higher than 0.05 and the Lambda exponent is positive. NA stands for not significant p-values.

4.4. Results discussion

In summary, the following findings can be highlighted. The BDS statistics reject the null of non nonlinearity (iid) in the residuals of ARMA model for the liquid bulk shipping series (table 3). This reveals that it may be possible to remain nonlinearity in the residuals, assuming that all linearity from the data has been eliminated appropriately applying ARMA filter. We investigate whether this nonlinearity is due to nonlinear deterministic chaotic dynamics or due to nonlinear stochastic dynamics. The results of the BDS test applied to the standardized residuals of the GARCH-type model indicate that the null hypothesis of iid is accepted. Hence, it can be concluded that the GARCH or EGARCH type models are adequate to capture all potential nonlinear dependence in the data. This was confirmed by a new test for the presence of chaos, based on the behavior of the estimated Lyapunov exponents. Negative significant Lyapunov exponents were obtained for this series. Thus, no chaotic component evidence is reported. In summary, our findings provide strong support for the presence of nonlinearity in the liquid bulk cargo series. However, we find evidence that the series behavior may be inconsistent with chaotic structure. On the other hand, the BDS test suggests that the dynamics of this series is non-linear stochastic. Using various criteria, we identify EGARCH (0,1) process as the model that best explains the nonlinearities.

5. Concluding remarks

In this research, we have analyzed the existence of nonlinearity and chaos in the monthly series of liquid bulk cargo in the Spanish ports. To this end, we conducted a complete study of the possible existence of a nonlinear and chaotic regime. Moreover, we have used recently developed procedures for testing nonlinearity and chaos.

In the first instance, the data were rendered stationary and appropriately filtered, to remove any linear dependence. Then we applied GARCH and EGARCH models to deal out with the presence of heterocedasticity. Finally, the residuals or standardized residuals, respectively, are tested for nonlinearity and chaos. We applied one of the most novel methods for detecting chaos. In contrast with previous methodology, this test can deal with noise.

The outcomes of our investigation using the BDS procedure provide strong support for the presence of non-linearity in the liquid bulk cargo series. However, we find evidence that the series behavior may be inconsistent with chaotic structure. The cause of nonlinearity appears to be conditional heteroskedasticity. Likewise, the BDS procedure results indicate that both the GARCH and EGARCH type models are adequate to capture all potential nonlinear dependence in the data. Using several accuracy criteria, we identify EGARCH process as the model that best explains the nonlinearities in the liquid bulk cargo.

Regarding previous research in this matter, Inglada-Perez (2010) studies the existence of non-linear dynamics and chaos in the Spanish maritime transport services for the period January 1992–December 2007. Using monthly time series data, in contrast with our results the study found that liquid bulk cargo did not show significant nonlinear dependence. This work updates and extends its findings by widening time span (1992-2013) and including economic crash in 2008. Discrepancies between the results of Inglada-Perez (2010) and this research could be due to the fact that a data set which includes recession period is used in this research. In this sense, asymmetric phenomena may arise in some economic series, which tend to behave differently when economy moves into recession rather coming out of it.

Our findings have many interesting practical implications because this study on existence of nonlinearity and chaos in liquid bulk time series will help to improve the quality and accuracy of forecasts on liquid bulk shipping. Specifically, the presence of stochastic nonlinearity in the data suggests that liquid bulk shipping models and forecasting models should account for the existing nonlinearities in the data, otherwise their results may be biased and highly misleading. For example, given the high costs as well as long-term and sunk character of investments in port infrastructure, policy makers and port managers need accuracy forecasts of liquid bulk cargo to decide on infrastructure projects. Regarding demand forecasting, GARCH and EGARCH type models appear as an optimum alternative to traditional linear forecasting methods such as the ARMA-methodology which are not able to handle and capture the volatility and nonlinearity that are present in the liquid bulk cargo series.

The conclusions derived from this research represent a breakthrough in the field of modeling and forecasting liquid bulk traffic in the Spanish ports and are particularly relevant for ports management and planning. Overall, our findings are of special interest for all the players involved in the shipping industry, including ship-owners, charterers, stevedores, brokers, policy makers, and regulators. Specifically, likewise. our forecasting results can help planners and policy-makers to take decisions on issues related to port infrastructure development and investment - such as construction of new terminals-, port operation, and freight rate (Sahu and Patil, 2017). In the context of planning process, because traffic forecasting is a critical part of every transportation planning for port investments. our findings should be of major interest in drawing up investment plans and infrastructure programs for the port system and for evaluating the recoverability of the investment. Specifically, given the large sunk costs as well as long-term and character of investments in port infrastructure, policy makers and port managers need accuracy forecasts of liquid bulk cargo to decide on infrastructure projects. In this line, Flyvbjerg et al. (2005) highlighted the relevance of demand forecasting citing the following causes: (a) estimates of the financial viability of projects are heavily dependent on the accuracy of traffic forecasting; (b) demand forecasts are the basis for socioeconomic and environmental appraisal of transportation infrastructure projects; (c) There is evidence that demand forecasting is a major source of uncertainty and risk in the appraisal of transportation infrastructure projects; (d) the forecasting results feed directly into impact appraisals such as cost–benefit analyses and environmental impact assessments; and (e) demand forecasts play a crucial role in the preparation of decision support to policy-makers in the field of transport planning.

Future research on the nature of liquid bulk shipping and forecasting of this remains an important issue, given that a scarce number of studies can be found. Further research is needed to examine other types of nonlinear models e.g. threshold ARCH model: ARCH integrated model and fractionally integrated model. As well the relationship between this variable and other relevant commodities and economic variables, such as oil price, might be considered through a multivariate GARCH mode (MGARCH) instead of working with separate univariate model.

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