Multifractal features of spot rates in the Liquid Petroleum Gas shipping market

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We investigate for the first time the spot rate dynamics of Very Large Gas Carriers (VLGCs) by means of multifractal detrended fluctuation analysis (MF-DFA) and rescaled range (R/S) analysis. Both non-parametric methods allow for a rigorous statistical analysis of the freight process by detecting correlation, scaling and fluctuation behavior regardless of nonlinearity issues. By applying different data-frequencies and a temporal framework, the Hurst exponents indicate that freight rates exhibit trend-reinforcement and persistence subject to limited time-dependency and controlled volatility. The found long-range dependence corroborates that a predictive freight model can be built undermining the efficient market hypothesis. Memory effects seem to each time build up until they are interrupted by seasonal transitions, stochastic events or cycles which all spark a sudden loss in correlations or increase in nonlinearities. The surrogate and shuffling data procedures demonstrate that, dependent on the data-frequency used, memory effects and fat-tail distributions should be contained differently in freight rate models.

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1. Introduction

Shipping is often held up as a volatile and unpredictable market, which is inspired by its derived nature with respect to global economics and trade. In addition come the own characteristics of the shipping business such as speculative and herding behavior, and shipbuilding cycles that are compounding its notorious volatility. These effects translate into diffused freight rate processes that at first sight seem to follow a random walk and difficult to predict.

The realization of the latter conjecture has been one of the reasons behind the shift in the maritime literature from building full scale simulation or econometric models to reduced forms or direct specifications of the freight rate process (Glen, 2006). The aim of scrutinizing the freight rate dynamics itself is basically to obtain its statistical properties. The benefit of such an exercise is that it supports the valuation (Tvedt, 1997) and the efficient pricing (Kavussanos and Alizadeh, 2002) of shipping assets under uncertainty. Shipping is one of the only industries having an active secondhand market where assets are traded. The price of a ship, like that of every other capital asset, depends on the ship's expected future profitability or the investor's expectation on the discounted cash flows or earnings (Engelen et al., 2006). This corollary has spawned the use of financial instruments and techniques that aim to find the best specification of freight rates.

In this paper we carry out a multifractal detrended fluctuation analysis (MF-DFA) and rescaled range (R/S) analysis to detect a myriad of correlation properties of LPG spot rate movements for Very Large Gas Carriers (VLGCs). Apart from introducing MF-DFA and R/S into the area of shipping economics, we investigate the seemingly undisclosed LPG shipping markets which have hardly been subject to academic research (Adland et al., 2008). The small size of the LPG markets compared to the dry cargo and the tanker markets as well as the lack of public data are presumably responsible. By researching the multifractal features and temporal correlations of gas freight markets, we are better in the position to assess the predictive ability of freight rate models and the efficient market hypothesis (EMH). Apart from valuation and pricing purposes, the specific analysis on gas freight rates could also underpin the pricing of gas freight derivatives or Forward Freight Agreements, the use of which is still embryonic but set to grow thanks to expanding LPG markets.

The organization of the paper is as follows. First, we scan the main findings and empirical results of previous research on ship market modeling. This will not only suggest the main and relevant properties of freight rates to be examined but also help reference our correlation results. As the analysis is done for the industrial LPG markets instead of the traditional dry and tanker markets, we can check whether market specific features will prompt different results. Second, we describe and
elaborate on the LPG dataset used. Third, we highlight the MF-DFA methodology and track the origins of multifractality. The R/S method frames the analysis in a temporal context and deepens the scope of the results in order to comment on time-dependent behavior, the importance of data-frequency as well as the repercussions on market efficiency. The results are contained in the conclusion and provide grounds for further research.

2. Freight market characteristics

In order to better understand the properties of freight rates, it is invaluable to denote the so-called shipping cycles inherent in the maritime industry (Stopford, 2008). These recurring cycles are born out the time lag between supply and demand adjustments and often magnified by herding behavior. If demand dynamics are buoyant and markets undersupplied, freight rates are high propelling shipowners to contract new ships, as everyone is loaded with cash and attracted by more fortunes to be earned. Quite often, too many ships are ordered so that an overhang of tonnage surfaces a few years later once the newbuilding are delivered. Freight rates are subsequently corrected until the oldest or unprofitable ships are scrapped and market conditions are restored again. Hence, shipping cycles tell us that high or low freight rates cannot persist. The consensus is therefore that freight rates are mean-reverting in the longer run (Tvted, 2003) for every shock in demand can be met in the course of time by the supply of additional tonnage.

The fact that there are always correcting forces at work does not preclude freight rates soaring or collapsing during shorter periods. The particular shape of the demand and supply function deems in this respect explanatory. Demand is in general assumed inelastic with respect to freight rates as seaborne transport is often the only viable option to carry the goods. Supply behaves fairly elastic as the fleet is homogeneous in cost structure (Strandenes and Adland, 2007) until the point where ships have to step up productivity and older uneconomical ships need be serviced. If these options have run out and capacity is fully utilized, the market becomes an auction and freight rates exhibit explosive behavior. Due to the inelastic demand function, every small change in the market balance will in turn impel large adjustments in rates, a phenomenon which is referred to as volatility clustering. This basically means that both small volatilities and large volatilities cluster together.

As in practice both the rather long-term self-correcting mechanisms and short-term bifurcations of freight rates conspire, it so proves that the discussion as to whether spot rates are stationary has not been resolved yet. We consent with Strandenes (1984) that in the long-run freight rates will revert towards long-run equilibrium costs of providing the transportation service. Answering to the issue of long-run freight rates will revert towards long-run equilibrium costs.

For the first time, we apply MF-DFA and R/S on spot rates in the LPG market of VLGC carriers. The above described freight market characteristics are the result of research on the competitive dry cargo and tanker shipping markets. The LPG market has some distinct features: the product LPG is not a raw material (such as e.g. oil, iron ore) but is gained by extraction from oil and natural gas wells. As the product is literally a by-product, the market is supply-driven and so behaves as a seller’s market confronted with expensive and limited storability (the same holds for the electricity markets, see e.g. Higgs and Worthington (2008)). The market is also stigmatized as being industrial and therefore less efficient because the players have a long-term operational focus and predominantly use period contracts (namely time charter contracts or Contracts of Affreightments (COAs)). This adds to the fact that the 57 mio ton LPG market is much smaller compared to the dry and tanker markets, constituting around 3 bio ton in 2008. VLGCs are estimated to have transported around 35 mio ton of LPG in 2008, whereof about 15% or 5.25 mio ton on account of spot contracts. It goes without saying that such a small market size induces swifter adjustments in freight rates. Opposed to this stands that LPG is an energy product used for heating, cooking and feedstock purposes in the petrochemical industry, so that substitutes are available that make seaborne demand more elastic which in turn smoothens product prices and freight volatility. Because of these unique features of the LPG market, it is interesting to see how correlations will behave and relate to the results obtained in dry and tank shipping.

3. Data

The time series contains the daily spot rates of VLGCs (80,000 Cbm loading capacity) on the benchmark Persian Gulf (Ras Tanura) to Japan (Chiba) route. A database was constructed with rates from 03.01.1992 to 24.06.2009, sourcing from Lorentzen & Stemoco AS and The Baltic Exchange. Fig. 1 plots the VLGC spot rates and their daily logarithmic returns. As this is the relevant price contracted on the market and the basis for pricing derivative contracts and many COAs. Moreover, TCE earnings correct for the less deterministic voyage costs (predominantly the bunker cost dynamics), which are governed by oil prices. We consider it valuable to integrate bunker dynamics in the analysis as it shapes the freight rate process as such.

As Table 1 sets out, the time series consists of 4536 observations, a large enough set to engage in multifractal analysis. Adland et al. (2008) used 727 weekly observations for the period 1992–2005 and applied a non-parametric Kernel estimator to capture the spot rate process. Another major distinction is that we use the spot rates as such, while in Adland et al. (2008) the time charter equivalent (TCE) spot rate was used. The latter is a calculated freight figure and obtained after subtracting voyage costs from spot rates. We prefer spot rate analysis as this is the relevant price contracted on the market and the basis for pricing derivative contracts and many COAs. Moreover, TCE earnings correct for the less deterministic voyage costs (predominantly the bunker cost dynamics), which are governed by oil prices. We consider it valuable to integrate bunker dynamics in the analysis as it shapes the freight rate process as such.

As charted in Fig. 2, the price increments are skewed to the right side showing excess kurtosis. The probability distribution function (PDF) of increments also shows a high degree of peakedness and rather fat tails, bearing out a clear departure from Gaussian normality and implicating that prices are subject to stochastic events. Indeed, the LPG market usually suffers from overcapacity and freight rates are bounded from below due to minimum service costs. Strong freight momentum is often short-lived and instigated by a temporary spike in Middle East exports. The empirical cumulative distribution curve supports the rejection of normality as the curve is clearly nonlinear. As
in Adland et al. (2008), we obtain the same result by the Jarque–Bera statistic in Table 1.

Zooming in on seasonality patterns can also yield interesting insight into the structure of freight rate processes as Kavussanos and Alizadeh (2001) pointed out. Fig. 3 highlights that freight rates tend to increase through the year in line with increased ship demand to replenish stocks in the period August–October until colder weather effectively kicks in and LPG deems too expensive. Stocks are used in the winter to satisfy the increased LPG consumption for heating, coinciding with less transport requirements and in turn a decline in rates. It is interesting to note that seasonality patterns especially strengthened during the last 5 years with LPG markets expanding. We were not able to derive obvious seasonal spikes from the traditional daily, weekly or monthly autocorrelation function (assuming Gaussian properties) that rather point to a slow price returns’ decay in time, hence, the amplitude of returns or volatility clustering.

For the sake of completeness, it is evidenced from Fig. 4 that daily gas returns are stationary as the standard deviation gets already saturated after an average time length of 20 observations. Hence, nonlinearities or volatility clustering would mainly surface in the very short run. The stationarity result, formally tested in Appendix A, is an important information not only to better understand and denote the correlation behavior in the next sections but also to compare gas to other shipping markets. Stationarity, although not a necessary condition, also adds to the reliability of the results obtained by R/S (North and Halliwell, 1994).

In line with general freight market characteristics, the data analysis of gas returns has demonstrated that we need to apply methods such as MF-DFA or R/S that can accommodate the adverse or nonlinear effects from volatility clustering, non-normality or fat tails.

4. MF-DFA methodology

MF-DFA is a generalization of the Detrended Fluctuation Analysis (DFA), which is a scaling analyzing technique providing a simple quantitative parameter – the scaling exponent \( \alpha \) – to represent the correlation properties of a time series. Unlike DFA which is only using the second moment, MF-DFA widens the scope to \( q \)-order moments depending on the time series length. Instead of one scaling exponent (monofractals), MF-DFA derives a continuous set of scaling exponents referred to as the singular spectrum. The benefit of MF-DFA is hence that it scales with multiple rules allowing for a more rigorous analysis of the data (Peng et al., 1994). In order to extract and reliably detect correlations, multifractal analysis among other things distinguishes trends from fluctuations at the same time that it can retrieve their origin and shape. Another benefit of scaling behavior tools is that one is able to deduce long-range correlations based on high-frequency data as the calculations are extrapolated across different time scales. This benefit will be checked by performing the analysis for different data-frequencies.

For there is a close link between the interpretation of the results and the MF-DFA methodology, we briefly describe the method used and refer to Kantelhardt et al. (2002) for more detail. The MF-DFA procedure is basically a five-step algorithm, the first three of which are identical to the conventional DFA procedure.

1. A profile \( y(k) \) of the time series \( x_k \) is created with \( k = 1...N \) and \( \bar{X} \) representing the average value.

\[
y(k) = \sum_{i=1}^{k} |x(i) - \bar{X}|
\]
2. The profile is divided into \( n_n \) non-overlapping boxes of equal lengths \( s \) with \( n_n = \text{floor}(N/s) \). In order not to disregard some data points to be left out, the procedure is repeated starting from the opposite end of the dataset.

3. In each box, the time series is fitted by using a local polynomial trend \( y_v \) of order \( v \). The corresponding variance of original versus fitted data is given by:

\[
F^2(v,s) = \frac{1}{N} \sum_{i=1}^{n_n} (y(N-(v-n_n)s+i)-y_v(i))^2
\]

with \( v = 1...n_n \). To obtain a DFA of order \( v \), the \( v \)-order polynomial function should be used, detrending the profile in each box in a different manner. DFA1, DFA2 or DFA3 point to the use of respectively a polynomial fit by a linear, a quadratic or a cubic function.

4. The \( q \)th order fluctuation function is obtained by averaging over all boxes. For \( q = 2 \), the standard DFA is retrieved. The index \( q \) can take any real value except zero.

\[
F_q(s) = \left[ \frac{1}{2n_n} \sum_{i=1}^{n_n} F^2(v,s)^{q/2} \right]^{1/q}
\]

5. By repeating step 3 for various time scales \( s \), the relation between the fluctuation functions \( F_q(s) \) and time scale \( s \) can be studied from the slope of the so-called log–log plot. The scaling behavior of \( F_q(s) \) is then determined for each \( q \). If the original time series \( x_k \) are power-law correlated, \( F_q(s) \) will increase for large values of \( s \), as a power-law:

\[
F_q(s) \sim s^{h(q)}
\]

Fig. 2. Comparison of the empirical/fitted normal histogram of price returns (left) and the empirical/Gaussian cumulative distribution function of price increments (right).

Fig. 3. Seasonality in VLGC spot rates.

Fig. 4. Standard deviation price returns \( \sigma \) versus box size \( s \).

The family of exponents \( h(q) \) describes the scaling of the \( q \)th order fluctuation function. For positive values of \( q \), \( h(q) \) describes the correlation behavior of segments with large variance \( F^2(v,s) \) or fluctuations. This is explained by the dominant impact of e.g. positive \( q \)'s and large variance segments on the average \( F_q(s) \). Analogously for negative values of \( q \), \( h(q) \) describes the scaling behavior of segments with small fluctuations. For stationary time series, the exponent \( h(2) \) is identical to the Hurst exponent. The family of exponents \( h(q) \) is referred to as the generalized Hurst exponents. It is interesting to note the richer specification in Eq. (4) than the DFA power-law relation \( F(s) \sim s^\alpha \). In monofractal series \( h(q) \) is independent of \( q \) as a single exponent is used. A typical characteristic for multifractal time series is that \( h(q) \) varies with \( q \). It can be shown (Sadegh Movahed et al., 2006) that the \( h(q) \) obtained from MF-DFA are related to the classical multifractal Renyi exponent \( \tau(q) \) by:

\[
\tau(q) = qh(q) - 1
\]
Another way to characterize multifractal series is hence the singularity spectrum \( f(\alpha) \), that is related to \( \tau(q) \) via a Legendre transform (Feder, 1988). With \( \alpha = \tau'(q) \), standing for the derivative of \( \tau(q) \) with respect to \( q \), we become:

\[
\alpha = h(q) + \frac{q}{q} \quad \text{and} \quad f(\alpha) = q(\alpha - h(q)) + 1
\]

(6)

Hereby, \( \alpha \) is the Hölder exponent or singularity strength denoting the singularities in a time series or monofractality. Singularity basically points at the rapid changes in the time series values for small changes in time. In the multifractal case, the different parts of the dataset are characterized by different values of \( \alpha \), or the singularity spectrum \( f(\alpha) \).

It is important to underline the difference between the above concepts as they will be used in the analysis of retrieving multifractal features of our dataset. Moreover, we will deepen the analysis by extracting the source or the origin of multifractality. In general, two types of multifractality exist: the first is due to different long-range temporal correlations or memory effects for small and large fluctuations. The second is due to fat-tailed probability distributions of variations (broadness of the PDF). Both types require a multitude of scaling exponents in order to fully describe the correlation behavior and to assess the true nature of the correlations. Two procedures will be applied to measure the contributions of both sources of multifractality. The shuffling procedure preserves the distribution of the variations but destroys any temporal correlations. The dataset becomes then a Markov process but with exactly the same fluctuation distributions. Surrogate data are used to detect the contribution of the fat-tailed increments on multifractality. We will use phase-randomized surrogates, thereby relaxing the non-normality of the distributions which was proposed by Theiler et al. (1992) to discover nonlinearities in time series. Phase randomization preserves the amplitudes of the Fourier transform but randomizes the Fourier phases. This procedure eliminates nonlinearities and holds the linear properties of the original time series (Panter, 1965). We will show and explain how the generalized Hurst exponents can be used to retrieve the type of multifractality.

5. MF-DFA-results

Following the steps of the MF-DFA procedure for the VLGC spot rate increments, we start by depicting Eq. (4) or the relation between \( F_q(s) \) and \( s \) for several moments of \( q \) in Fig. 5. The log–log plot demonstrates the fractal dimension or power-law for \( q = -10 \) to \( q = 10 \) signaling that the data are scale-invariant or fractal.

As the time scale \( s \) gets larger, it shows that the behavior of the time series fluctuations for different values of \( q \) evolves to the same \( F_q(s) \). In fact there is a time scale large enough at which, regardless of the value of \( q \), the same variance is reached for both small and large fluctuations. If a small box scale is used, the behavior of small and large fluctuations is different. By zooming in on the log–log plot, the benefit of using several fluctuation functions is that several scaling regimes or regions with uniform scaling can be distinguished (Uritskaya and Serletis, 2008). A crossover-point or a sudden change in the slope of the fluctuation function (as visual representation of the scaling exponent) marks a change in regime.

- A first strong memory regime that can be detected lasts around 4 trading days (\( s = 2 \)) given by the steep slope of the fluctuation function. The reason behind the strong presence of memory effects is probably the formation of spot rates itself. Everyday a broker panel consisting of 8 shipping companies postulate an estimation of the spot rate, which is then averaged into the Baltic Gas Index. As there are not enough spot transactions, quite often the rate from the previous day is repeated with a minor or otherwise a significant adjustment. It is mostly on Friday that shipbrokers really assess the market balance and freight rates when they send out their weekly reports. This explains that in the very short run spot rate increments display dominant persistent behavior.

- A second scaling regime goes from \( s = 2 \) to \( s = 6 \) that translates into 60 trading days, ca. 84 days or approximately a season. Seasonality in the gas markets is well-known but not to the extent it would really impact on freight rates.

- A third scaling regime surfaces in the period \( s = 6 \) to \( s = 8 \) encompassing 192 trading days, ca. 269 days or three seasons. A check of the time series shows that this period often coincides with a cycle in which rates have increased and decreased again. Such a cycle comprises e.g. the start of the spring to the winter encapsulating the surge and fall in rates during the summer period.

The log–log plot is often useful to visually retrieve a specific trend in the increments. In our case, apart from the strong very short run scaling regime that is inspired by the freight rate stipulation process, there is no clear trend that emerges. Or, there are enough trend functions that could be used to mimic the behavior of the freight rate fluctuations. Adland et al. (2008) conclude via a Kernel approach that the weekly VLGC freight rates can be approximated by a linear model. Our analysis confirms indeed that this can be used, but does not uniquely retain this as the only viable trend to describe the considered freight rate process.

The above results make it redundant to estimate the Hurst exponents and apply a straight line regression based on Eq. (4) for each value of \( q \). In the literature (Peng et al., 1994), both \( h(q = 1) \) and \( h(q = 2) \) are used to denote the Hurst exponent \( H \). The fitted linear Hurst exponent of 0.67 reveals that the freight rate process is correlated or that a price increase in the past is more likely to be followed by an additional price increase than a price decrease. Hence, daily spot rate movements are persistent \( (h(q) > 0.5) \) and subject to trends. The Hurst exponent can also be interpreted as a measure of the bias in the standard or fractional Brownian motion \( H = h(q = 2) - 1 \). Hence, the deviation from the random walk provides interesting information on the volatility and risk inherent in shipping. A relatively high Hurst exponent underpins the relatively smooth trend and less or controlled volatility. As pointed earlier, for positive values of \( q, h(q) \) especially describes the segments with large variance or fluctuations. These observations indicate that the trending process is dominant in periods where rates are increasing or decreasing for a period of time. This persistent effect is stronger than the mean-reversion or anti-correlation \( (h(q) < 0.5) \) process of spot rate movements.

The above elements have important economic repercussions on market efficiency and forecasting power of models. Higher Hurst exponents point to developing markets or markets in which the EMH does not hold. The EMH, bluntly stated, postulates that in competitive markets all information is instantaneously reflected in prices and it is not possible to structurally beat the market. The consequence is that prices should follow a random walk \( (h(q) = 0.5) \) and markets cannot be predicted. The larger \( h(q) \) deviates from 0.5, the less noise in the
system or the more time series are (anti-) correlated so that the predictive ability of models rises too. As Adland et al. (2008) also find, gas freight rates can be specified by a relatively easy model: integrating the above seasonal and cyclical effects should suffice to obtain e.g. a forecastable model. The ability to have a model at hand however shifts the question as to whether the market can actually be exploited as such. This question can better be answered if the origins of multifractality are examined and the EMH is put in a temporal context.

Instead of using one Hurst exponent or measure of correlations, the analysis can be enriched by applying the different multifractal scaling exponents visualized in Figs. 6 and 7. The strong dependence for the original dataset between \( h(q) \) compared to \( q \) surfaces that the price increments are scale-invariant. The strong measure of multifractality is revealed by the broad range of Hurst exponents, i.e. the difference between maximum and minimum values. Monofractal time series are associated with a linear \( \tau(q) \) plot, while multifractal series expose spectra nonlinear in \( q \). The higher the nonlinearity in spectrums, the stronger the time series are multifractal. The steep slope in the \( \tau(q) \) plot in this respect confirms the presence of multifractality especially in the small variance segments with \( q < 0 \). Another signal of multifractality is demonstrated by the curvature in the singularity spectrum \( f(\alpha) \) versus \( \alpha \). Both the broad spectrum of \( f(\alpha) \) and the rapid modified values of the H"older exponent underline the richness of our dataset.

Apart from underlining the complexity of the dataset, the value in these figures is especially in its ability to track the origin of fractility and the true nature of the correlation results. Both the \( h(q) \) and the \( \tau(q) \) plot indicate that the multifractal nature of the price increments is mainly due to memory effects rather than a fat tail, given by the wider departure of the shuffled data from the original dataset. This holds both for the small and large variance regimes with respectively \( q < 0 \) and \( q > 0 \). As stated earlier, this is among other things inspired by the manner in which freight rates are often marginally adjusted every day. When freight markets are in the doldrums with significant overcapacity – something which frequently occurs in the industrial gas market – the bunker costs often determine the lower bound of the freight rate. Spot rates remain dull and hardly move as brokers have no other grounds to quote other rates. This result in a strong memory effect and explains why shuffling the time series has a strong bearing especially in regimes with \( q < 0 \). In large variance segments or regimes where freight rates move in large steps, the effect might be less simply because of the reduced frequency of freight markets being tight or buoyant. The surrogate curve in the \( h(q) \) and \( \tau(q) \) panel is almost linear, strongly pointing to monofractality. The surrogate procedure hence tells that nonlinearities are present in both the low and high variance segments.

It is generally acknowledged that the singularity spectrum provides the most detailed test to represent the complexity and the types of multifractality. The reduced curvature of the dual shuffled (and surrogate) price increments clearly point that memory effects are present as the singularity strength \( f(\alpha) \) of the higher values for the H"older exponent \( \alpha \) is destroyed. It is interesting that especially for the higher values of the H"older exponent, characterized as regions with more regularity, the correlations of the increments are destroyed by shuffling. For data behaving more singularly or irregularly, the
correlations seem to persist. Again we do witness that the randomized surrogates lead to a monofractal series and the removal of all nonlinearities. The small width of the fractal even resembles that of a Brownian motion. Nonlinearity and fat tails hence have to be integrated in freight rate models.

The above findings are all characteristics of our daily price increments. Quite often, although freight rates are quoted every day, instead of daily observations weekly or monthly time series are used for research to correct for the dominant short-term memory effects. If the complete exercise is redone for weekly and monthly freight movements, some interesting conclusions surfaced. By using weekly observations Fig. 7 in this respect shows that the time series do not truly have a memory process in place but are independent. Fat tails and nonlinearities however will still be present in almost the same fashion as with daily analysis. If monthly observations are used, it is striking that both the shuffling and surrogate procedure demonstrate that memory effects and fat tails disappear. Changing the frequency of the dataset will hence significantly alter the time series characteristics. This is also corroborated by the different Hurst exponents obtained for weekly and monthly increments. The weekly and monthly generalized Hurst exponents are then respectively 0.52 and 0.44 pointing in turn to a random walk or mean-reversion. By using weekly spot earnings for a smaller dataset, Adland et al. (2008) obtained for weekly and monthly increments. The weekly and monthly generalizations of the Hurst exponent in temporal fashion is the traditional R/S method (see Edgar (1996) for a thorough overview) that in addition allows for a relative easy scan of the results obtained thus far. Despite the known drawbacks (bias in estimating the Hurst exponent, discontinuous box counting), the R/S technique is still widely applied, especially when the price returns are stationary rendering the results more reliable (North and Halliwel, 1994). The calculation can be summarized as:

\[
R/S(N) = \frac{1}{N} \left( \max_{1 \leq i < N} \left( \sum_{j=1}^{N} (x(i) - \bar{x}) \right) - \min_{1 \leq i < N} \left( \sum_{j=1}^{N} (x(i) - \bar{x}) \right) \right) \tag{10}
\]

In this classical compact form, \(\alpha_n\) refers to the sample standard deviation with equal box size \(N\), while the first and the second terms on the right hand side refer respectively to the maximum and the minimum of the partial sums of the first \(i\) deviations of \(x(i)\) from the sample mean. Mandelbrot and Wallis (1969) highlighted the relevance of R/S with respect to detecting memory effects and scaling behavior, advancing the following power-law relation (analogous to Eq. (4)) to hold for a sufficiently large size of \(N\):

\[
\frac{R}{S(N)} \sim N^{-\frac{1}{H}} \tag{11}
\]

By computing Eqs. (10) and (11), the R/S analysis yields approximately the same Hurst exponents as MF-DFA for the entire sample as Table 2 corroborates. It is interesting to proceed to the calculation of the time-dependent Hurst exponent \(h(t)\) to better denote these general outcomes and to smoothen the effect from outliers. Instead of just providing one number to characterize the global properties of time series, the scaling exponent or correlation behavior is put in a progressing time window allowing for tracking the time-variability of the Hurst exponent. In the case of a time window of 1024, the window starts progressing after 1024 observations and returns 4534–1024 or 3510 Hurst exponents. The method is described in Peng et al. (1994), and applied in e.g. Alvarez-Ramirez and Escarela-Perez (2010) using a seven-day rolling window. In Table 2, we have used several window lengths to account for the effect of different time scales and to better follow the evolutionary path or stability of \(h(t)\). The selection of exactly 16, 32, . . . , 2048 observations is inspired by the technical details of the R/S method. Using these daily box sizes, the time series need not be broken into smaller blocks as e.g. 1024 or 256 is an integer multiple of 2. The results clearly confirm the persistent memory effects. Comparing a box size of 16 to 1024 e.g., it is remarkable that \(h(t)\) only decreases with about 0.1, pointing to long-range dependence of freight rate movements. Also when weekly or monthly time scales are used can we notice that positive correlations are dominant on smaller scales, only to temper slowly as time increases. The tabulated exponents hence show the relativity of using one single exponent to characterize time series.

In the next step, we confronted \(h(t)\) across time scales with the actual freight rates and freight rate movements to thoroughly check how deviations and correlations behave over time. The main focus was on the daily results as these form the richest dataset at the same time that they still allow to filter long-range dependence. The analysis reveals that interesting results could be derived from the daily correlations stretched over one (256 trading days) or two (512 trading days) years. Taking account of the progressing time window, the plotted \(h(t)\) in Fig. 8 moves strikingly well in concert with the freight rates in Fig. 1. This congruence among other things demonstrates how shipping cycles can be recovered over time. A first cycle is detected from 1993/1994 lasting to 1996/1997 with correlations increasing through the cycle to subsequently reduce and disappear as the cycle ends or another cycle emerges. A second cycle shapes through 1998 to 2003: starting in 1998, the top reaches in 2001 and disappear as the cycle ends or another cycle emerges. A second cycle shapes through 1998 to 2003: starting in 1998, the top reaches in 2001 and the collapse follows in 2002. The third cycle begins end 2003 and slowly progresses to reach the climax in the summer of 2008 when the rates were all-time high after which the market crashed over night, articulated by a steep reduction in \(h(t)\). It is especially sudden market changes, exogenous effects (e.g. Asia crisis) or shipping cycles ending (e.g.

### Table 2

<table>
<thead>
<tr>
<th>Box size</th>
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<th>Weekly</th>
<th>Box size</th>
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<tr>
<td>Total</td>
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<td>Total</td>
<td>Total</td>
<td></td>
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<tr>
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profileration of overcapacity) that are well captured by a significant loss in memory effects or the reduced Hurst exponents. As in Alvarez-Ramirez and Escarela-Perez (2010), we also witness that such phenomena trigger nonlinearities and abrupt price changes that induce a fall in correlations. During cycles or period of times with no stochastic transitions correlations seem to build up and persist over time. This underpins the results from Figs. 6 and 7, in which memory effects were most important in periods with low variance or more regularity. Likewise results can be derived from the weekly $h(t)$ over 52 trading weeks, although the pattern is less pronounced than with daily fluctuations.

By using a smaller semi-annual box size in Fig. 9 variations within years can be investigated. The same cyclical indications (underlined in Fig. 9) can be retrieved as in the case of annual cycles, reflected by the sudden decline in $h(t)$. In addition, other moments can be spotted at which correlations swiftly tumble. A closer look on these effects show these events can be inspired by different forces. One reason can be cycles that do not fully materialize. As Stopford (2008) describes, history has shown that a full shipping cycle typically consists of 4 phases – trough, recovery, peak, collapse – some of which do not always materialize due to stochastic events such as canal closures, wars etc. that strongly affect demand and supply fundamentals. The market has to be rebalanced before the cycle continues or a new cycle emerges. It is hence difficult to assess whether freight rates fall precipitately or refine equilibrium. This clearly happened in the period 1998–2004 in which the market was several times on the verge of collapsing before it really did. What can be learned from these observations is that uncertainty or a lack of market balance leads to more nonlinearities or secular price behavior that in turn translate into reductions in $h(t)$.

Another force at work are the seasonal variations that return. By mirroring Figs. 9 and 10 to freight fluctuations, it seems the seasonal patterns are a recurrent theme although it does not easily show from the correlations. This can be due to the dominance of random events, or arbitrage in the product market that quickly causes ships to be repositioned with repercussions on freight rates. Another more important factor to consider is that market participants already anticipate the stockbuilding period of August–October and winter spell. Seaborne gas transport is a derived product from LPG demand and supply, markets in which traders heavily try to reap the benefits from exploiting markets in contango (stockbuilding) and back-wardation (winter). This is probably why we often do not see a shift in scaling behavior in the seasons itself but more when the transitions from one season to another take place. The bias or the deviation from the random walk is hence generated by the market participants who react and anticipate seasonality. Especially in November and March do we locate a loss in correlations or increased nonlinearities. November marks the month in which stocks have been replenished and occasional winter transport requirements are to be determined. The latter involves speculation about winter spell as e.g. cold weather in January in Japan needs be anticipated by a Middle East-Japan voyage that takes around 36 days. A likewise regime switch occurs in March when the market is coming out of the winter and usual trading patterns are restored. The previous results can hence be confirmed that markets in lack of information or transition are characterized by a decrease in $h(t)$. These recurrent changes could be accommodated by a regime-switching model as proposed in Huisman and Mahieu (2003) or Higgs and Worthington (2008).

The results from the more detailed box size analysis allow to further add to the general results obtained by MF-DFA and R/S. It is striking that both for the large and the small time scales the memory effects are persistent at the same time that they are subject to limited time-dependency. The daily $h(t)$ in Figs. 8–10 never seem to reverse to anti-cyclical movements or a random walk. The fact that this resonates to larger periods corroborates long-range dependence. If a general approach is desired, it shows that for a box size of 1024 observations or approximately 4 years $h(t)$ oscillates between ca. 0.64–0.74 supporting the controlled and smooth volatility of freight rate increments or limited time-dependency. A side note in this respect is that across the bigger time windows we could not find an obvious relation between the rather stable persistence of the Hurst exponent and volatility, measured by the standard deviation of the price returns. Annual cycles or longer periods with higher or lower volatilities would hence have no marked impact on memory effects contained in the freight increments. This absence of time-varying behavior supports that parametric forms can be used to describe global freight rate patterns, which is in line with the findings of Adland et al. (2008).

7. Market efficiency

Summarizing the results throughout this paper, the scaling and multifractal results validate that freight rate forecasting is a feasible task because of returning phenomena of cycles (3–4 years) or long-range dependence and a lack of time-variability (in volatilities and correlations) over longer periods. The trend-reinforcing behavior in freight rate movements is dominant and only abruptly halts by a stochastic event or a changing regime (e.g. seasonal transition) that interrupts the ongoing cycle. Nonlinearities therefore are often short-lived and explain the presence of fat tails, the loss in memory or value of the Hurst exponent. The speculative and anticipative behavior of market participants in itself creates a bias or noise that causes $h(t)$ to secularly deviate from a random walk.

From a theoretical point of view, there are hence some elements that interfere with efficient markets. The strongest argument is given by the steep very short run scaling regime in the log–log plot that underpins a very high Hurst exponent. Wang et al. (2010) in addition argue that the different results across fluctuation functions also affirm market
inefficiency. Daily, weekly and even monthly analysis confirmed the persistent behavior over several years. The fact that \( h(t) \) is generally not decreasing over time means that the gas markets have not become more efficient but remained in their developing stadium. Following Wang et al. (2010) on \( h(t) \) regimes, gas freight returns rarely approach a random walk or switch to mean-reversion (only in weekly and monthly temporal analysis) questioning efficient market functioning. The question then shifts as to whether market participants can exploit these inefficiencies in practice.

LPG traders already try to exploit seasonality in energy markets by selling and buying LPG at the right moment. It seems shipowners and charterers could do the same thing by being short or long in tonnage at the right moment, especially in periods of seasonal transitions that introduce a new scaling regime. The only difficulty that remains is that VLGC shipping markets lack liquidity. Although spot rates are quoted on a daily basis, quite often there are only a few spot transactions done per month. This renders it tedious to exploit the strong persistence in the very short run, and also feeds the discussion as to whether the VLGC market really needs daily freight quotations. As the positive correlations stretch out over annual cycles irrespective of the data-frequency applied, there is evidence that markets can technically be beaten by strategic behavior. The fact that the freight service is non-storable and that freight contracts are easily transferable to other charterers or shipowners add to this.

8. Concluding remarks

In this paper a multifractal approach is applied to analyze VLGC freight rates. In line with maritime theory, spot rate changes demonstrate positive skewness and excess kurtosis. It is in this respect welcome that MF-DFA and R/S can deal with nonlinearities inspired by non-normality, fat tails, volatility clustering and seasonality. MF-DFA in addition uses multiple scaling rules and detrends the dataset to overcome short-term non-stationarities. The strong evidence of stationarity for the price returns adds to the reliability of the R/S results, exacerbated by the fact that the results are analogous to those obtained by MF-DFA. In order to correctly interpret the results and derive conclusions, the correlation analysis was thoroughly put in a temporal context with varying data-frequency (daily, weekly or monthly observations) and time scales to distinguish between short and long-run time series behavior.

The different approaches used clearly indicated multifractal features of the freight rate process inspired by memory effects and fat-tailed behavior, the latter of which significantly behave differently when the data-frequency is changed. The different multifractal exponents and the singularity spectrum show that by using weekly observations the memory effects disappear while monthly returns would in addition also delete the fat tails and render the time series monofractal. The selected data-frequency hence affects the type of model (e.g. linear or not) that should be used to specify freight rates. We mainly focused on the daily observations as this forms the richest dataset at the same time that it was evidenced that MF-DFA or R/S are then still able to display long-range dependence and return the best results. Market specific characteristics thereby prompt different correlation results than those obtained from analysis of other shipping markets.

For the entire sample, the daily Hurst exponent of 0.67 varying between 0.61 and 0.71 indicates that freight rate movements exhibit smooth trend behavior and persistence, underlining the controlled volatility and memory present in the time series. Moreover, there seem to be no obvious relation between the persistence of the Hurst exponent and standard deviation or volatility over time. The absence of strong time-dependent behavior facilitates the use of parametric functional forms to describe freight rate processes.

In the very short run, the log–log plot clearly visualized that the memory effects of freight rate increments are artificially high due to the nature of the freight rate stipulation process and the lack of corresponding transactions in practice. From the time-dependent quantification of the Hurst exponent, it appears that correlations are trend-reinforcing over
longer periods even resonating over several years or annual cycles. There is a clear tendency of positive correlations over time that are interrupted by seasonal market transitions, stochastic events or the end of the shipping cycle (overcapacity and subsequent fall in rates) emerging. This is each time reflected by a sudden loss in the value of the correlation exponents or by increased nonlinearities popping up, after which a new regime of memory effects is built up again.

The strong persistent behavior in the freight rate process with hardly any switch to a random walk or mean-reversion process are elements that add to the capacity to build a forecast model and as such interfere with the EMH. A lack of liquidity in the VLGC market renders it difficult to exploit inefficiencies in the short run while shipowners and charterers could potentially benefit in the longer run by strategically positioning themselves being short or long in tonnage.

The above findings pinpoint that short-term and long-term effects conspire and that multifractal features should be taken up in freight rate models. In order to fully capture the short-term effects, specific types of autoregressive (see e.g. Bowden and Payne, 2008) or fractional Brownian motion models could be designed but likely not without introducing concepts from jump processes to account for sudden large discrete movements. Ideally, a functional form needs to be developed that also encapsulates the long-term mean-reversion characteristics inspired by cycles. The building of a tailor-made error correction model or a mean-reverting/regime-switching model (see e.g. Huisman and Mahieu, 2003; Higgins and Worthington, 2008) are in this respect interesting avenues for further research. It would not only allow to better specify LPG spot rate processes and develop a derivatives formula but so too would it help assess the asset values of gas carriers and cater for profitable investment strategies.

Appendix A. Stationary test

As set out in the introduction, it is not easy to determine as to whether time series are stationary due to issues of sample size or data-frequency. Several formal tests are commonly used in practice. The traditional augmented Dickey Fuller (ADF) test is a unit root test with the null hypothesis claiming that the series is non-stationary. In line with the literature, the test is performed for both the intercept (constant), and intercept with trend. The lag length is automatically computed based on the minimization of the Schwarz information criterion. The Phillips and Perron (PP) test is comparable to the ADF test but makes a non-parametric correction to the r-test statistic to capture the effect of autocorrelation present when the underlying autocorrelation process is not AR(1) and the error terms are not homoscedastic. The null hypothesis of the KPSS test developed by Kwiatkowski et al. (1992) investigates whether the time series are stationary around a deterministic trend. The ADF and PP results in Table 3 clearly point to stationary freight rates and their returns. The KPSS test yields mixed results for the original freight rates, as the test with constant term rejects stationarity for all considered confidence levels. A closer look on the test reveals that the outcome is dependent on the bandwidth selection method chosen, which is, bluntly stated, important to determine the weight of the time lags used in the estimation. If the parametric Andrews (1991) test is used instead of the conventional non-parametric Newey and West (1994) test, the KPSS test results remain inconclusive: stationarity would then be confirmed for the constant version, while rejected for the constant with trend version for all confidence levels. The most important conclusion is that all three tests unambiguously support stationarity for the freight rate returns.

References
