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

Steve Engelen^{a,*}, Payam Norouzzadeh^b, Wout Dullaert^{c,d}, Bahareh Rahamani^b

^a*Lorentzen & Stemoco AS, 4 Lilleakerveien, Oslo 0216, Norway*

^b*Christian Albrechts University of Kiel, 40 Olshausenstraße, Ravensberg 24118, Germany*

^c*Institute of Transport and Maritime Management Antwerp, 24 Keizerstraat, Antwerp 2000, Belgium*

^d*Antwerp Maritime Academy, 6 Noordkasteel Oost, Antwerp 2030, Belgium*

Abstract

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 methods allow for a rigorous statistical analysis of the freight process by detecting correlation, scaling and fluctuation behavior regardless of (non-)stationarity or nonlinearity issues. By so doing, the generalized/classical and time-dependent Hurst exponents indicate that freight rates exhibit trend-reinforcement and persistence. Rates seem subject to controlled volatility and can be approximated by different types of trend functions. The origins of multifractality are mainly coming from memory effects rather than fat-tail distributions.

JEL classification: C14; C32; C63; Q40

Keywords: MF-DFA; R/S; LPG; Freight Rates; Hurst exponent

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 (Haralambides et al., 2005). These effects translate into diffused freight rates 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. An extensive research overview of shipping modeling can be found in Beenstock and Vergottis (1993) or 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

* Corresponding author: Lorentzen & Stemoco AS, 4 Lilleakerveien, Oslo 0216, Norway.

E-mail address: steve.engelen@lorstem.no (S. Engelen)

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 (Fama, 1970; 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 statistical properties of the LPG spot rates 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, apart from Adland et al. (2008) and Engelen and Dullaert (2009), have not been subject to any academic research. 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. Apart from valuation and pricing purposes, the specific analysis on gas freight rates could 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 MF-DFA 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 is set out to confirm and deepen the MF-DFA analysis. The results are contained in the conclusion and provide grounds for further research.

2. Freight Market Characteristics

In order to better understand the statistical properties of freight rates, it is invaluable to denote the so-called shipping cycles inherent in the maritime industry (Stopford, 2008). These returning 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 newbuildings 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 subsist. The consensus is therefore that freight rates are mean-reverting in the longer run (Tvedt, 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 deem 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. Tinbergen (1934) and Hawdon (1978) proposed even exogenous demand, while Lensberg and Rasmussen (1992) and Engelen et al. (2006) postulated a stochastic demand function. Supply behaves fairly elastic as the fleet is

homogeneous in cost structure (Stranden 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 (Tvedt, 2003b). Koekebakker et al. (2006) rightly concluded that in order to answer the issue of stationarity, it is necessary to include nonlinear versions of e.g. the Augmented Dickey–Fuller (ADF) test. Goulielmos (2009) thoroughly reviewed past research and basically rejected all nonlinear tests or specifications of freight rates, such as the use of ARCH and GARCH models (Kavussanos, 1997; Jing et al., 2008). Not only nonlinearities but also the rejection of normality based on the Jarque-Bera test, and excess kurtosis and skewness point to the presence of memory effects and the misleading nature of ARCH and GARCH models with respect to stationarity. An improvement can already be attained by a fractional integrated version or FIGARCH models that can better display long-range correlations (Carbone et al., 2004). We consent with Zannetos (1966) and Stranden (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 stationarity is hence an empirical question as the time coverage of the sample data used can alter the results (Adland and Cullinane, 2006).

The benefit of MF-DFA and R/S is that they allow for determining the multifractal characterization of both non-stationary and stationary time series. In addition, all the main nonlinear characteristics of rich datasets such as fat-tailness of probability distributions and volatility clustering are factored into the concept of MF-DFA and R/S. This is important both for practical and theoretical reasons. If spot rates exhibit multifractal behavior, these properties need be considered in e.g. the pricing of derivative contracts. Also, the origins of multifractality can be traced, revealing whether long-range correlations of price fluctuations or rather fatness of the price increments are dominant.

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. 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 57mio ton LPG market is much smaller compared to the dry and tanker markets, constituting around 3mio ton in 2008. VLGCs are estimated to have transported around 35mio ton of LPG in 2008, whereof about 15% or 5.25mio ton on account of spot contracts. It goes without saying that such a small market size induces swiftness 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 smoothenes product prices and freight volatility (Engelen and Dullaert,

2009). Because of the unique features of the LPG market, it is interesting to compare the results with those obtained in dry and tank shipping. Throughout the paper we also benchmark the analysis with Adland et al. (2008), the only analysis done on the LPG freight rate patterns thus far.

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. Figure 1 plots the VLGC spot rates and their daily logarithmic increments (that is, $\ln P(t)/\ln P(t+1)$). Logarithmic returns are used as they are a convenient way to show daily fluctuations in prices.

Fig. 1. VLGC spot rates (\$/ton) and price increments.

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.

Table 1

Descriptive statistics VLGC spot rates.

	Database	Log returns
Observations	4536	4535
Mean (\$/ton)	30.91	-6.798 e-005
Maximum (\$/ton)	81.64	0.1105
Minimum (\$/ton)	12.90	-0.1440
Std. deviation	11.05	0.0166
Skewness	1.132	11.6984
Kurtosis	1.64	8.6984

As charted in figure 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. 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 (right panel) curve supports the rejection of normality as the curve is clearly nonlinear. Adland et al. (2008) obtain the same result by the Jarque-Bera statistic (Bera and Jarque, 1981).

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

Zooming in on the seasonality patterns can also yield interesting insight into the structure of freight rate processes as Kavussanos and Alizadeh pointed out (2001). As LPG is consumed for heating, the winter period is usually anticipated by stock building in the third quarter when traders strive to benefit from energy prices in contango. The benefit of MF-DFA is that it actually accounts for possible (seasonal) trends as it per definition detrends the dataset. Moreover, the autocorrelation function (ACF) in figure 3 does not reflect any important seasonality or returning patterns but rather points to the price returns' decay in time. The fact that the absolute returns remain significantly positive over many lags rather corresponds to persistence of the amplitude of returns or volatility clustering.

Fig. 3. Autocorrelation function price returns.

The ACF can also be used to detect the (non-)stationarity of time series. As the ACF starts at a rather high value and declines very slowly towards zero as the lag lengthens, a first signal of non-stationarity is evidenced (Damodar, 2003). Moreover, figure 4 indicates that the standard deviation of gas price returns versus timescale or box size s is not saturate. Adland et al. (2008) found evidence for stationarity in TCE earnings. The fact that we reveal a non-stationary process can be due to the increase of the mean freight rate over time due to higher bunker costs that hike the lower bound of freight rates. This effect is removed in Adland et al. (2008) as earnings are considered. Another reason for the difference in results could be due to the use of high frequency date that bifurcate more than weekly observations.

Fig. 4. Standard deviation price returns σ versus box size s .

Whatever the exact motivation, in a non-stationary situation, a spurious set of correlations might be detected, making that a direct calculation of correlation behavior does not lead to reliable results. We then need to apply methods which are insensitive to non-stationarities such as MF-DFA or R/S.

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 α – 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.

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 $k = 1 \dots N$ and $\bar{x}$ representing the average value.

$$y(k) = \sum_{i=1}^k [x(i) - \bar{x}] \quad (1)$$

2. The profile is divided into n_s non-overlapping boxes of equal lengths s with $n_s \equiv \text{floor}(N/s)$. 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:

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

with $v = 1 \dots n_s$. 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.

$$F_q(s) = \left[\frac{1}{2n_s} \sum_{i=1}^{2n_s} F^2(v, s)^{q/2} \right]^{1/q} \quad (3)$$

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:

$$F_q(s) \sim s^{h(q)} \quad (4)$$

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 scaling or 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 (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:

$$\tau(q) = qh(q) - 1 \quad (5)$$

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:

$$\alpha = h(q) + qh'(q) \quad \text{and} \quad f(\alpha) = q[\alpha - h(q)] + 1 \quad (6)$$

Hereby, α 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 or position (Kulkarni et al., 2005). In the multifractal case, the different parts of the dataset are characterized by different values of α , or the singularity spectrum $f(\alpha)$. For the sake of completeness, it must be noted that $h(q)$ is different from the generalized multifractal dimensions $D(q)$ that are sometimes used instead of $\tau(q)$. While $h(q)$ is independent of q for a monofractal time series, $D(q)$ still depends on q in that case.

$$D(q) \equiv \frac{\tau(q)}{q-1} = \frac{qh(q)-1}{q-1} \quad (7)$$

It is important to underline the difference between the above concepts as they will all 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. We will apply two procedures 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-Gaussianity 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).

The generalized Hurst exponents can be used to retrieve the type of multifractality. If the multifractality only belongs to long-range correlations, $h_{shuf}(q) = 0.5$, because the shuffling procedure destroys the long-range correlation. If the multifractality is inspired by a broad PDF, $h(q)$ should be independent of q . If both types of multifractals are present, the shuffled and surrogate time series will yield weaker multifractality than the original dataset. Apart from the Hurst exponents, benchmarking the original fluctuation functions $F_q(s)$ with the shuffled $F_q^{shuf}(s)$ and surrogate $F_q^{sur}(s)$ substitutes might be more intuitive, articulating directly the contribution of long-range correlations or broadness of the PDF. The differences can be observed in a plot of the ratio $F_q(s)/F_q^{shuf}(s)$ and $F_q(s)/F_q^{sur}(s)$ versus s . Since the anomalous scaling due to a broad probability density affects $F_q(s)$ and $F_q^{shuf}(s)$ in the same way, only multifractality due to correlations will be expounded in $F_q(s)/F_q^{shuf}(s)$. The corresponding scaling behavior of the ratios is calculated as:

$$F_q(s)/F_q^{shuf}(s) \sim s^{h(q)-h_{shuf}(q)} = s^{h_{cor}(q)} \quad (8)$$

$$F_q(s)/F_q^{sur}(s) \sim s^{h(q)-h_{sur}(q)} = s^{h_{PDF}(q)} \quad (9)$$

If only fatness of the PDF is responsible for the multifractality, one should find that $h(q) = h_{shuf}(q)$ and $h_{cor}(q) = 0$. On the other hand, deviations from $h_{cor}(q) = 0$ demonstrate the presence of correlations, and q dependence of $h_{cor}(q)$ points that long-range correlations are responsible for multifractality. If only correlation multifractality exists, $h_{shuf}(q) = 0.5$. Mostly, both correlation and distribution multifractality are present, or $h_{shuf}(q)$ and $h_{sur}(q)$ will depend on q .

5. Results

Following the steps of the MF-DFA procedure for the VLGC spot rate increments, we start by depicting the relation between $F_q(s)$ and s for several moments of q in figure 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.

Fig. 5. Fluctuation functions $F_q(s)$ versus box size $\log(s)$ for $q = -10$ to 10 .

As the time scale s gets larger, it shows that the behavior of the time series fluctuations for different values of q evolve 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. The log-log plot is often useful to visually retrieve a specific trend in the increments. In our case, 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 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; Taqqu et al., 1995), 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, spot rates 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 $H = h(q = 2) - 1$ (Ossadnik et al., 1994). 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. Together with the possible use of a linear trend reflected in the log-log plot, our results do not interfere with Adland et al. (2008) who found that VLGC freight earnings could be approximated by a linear stochastic model. 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 effect is stronger than the expected mean-reversion or anti-correlation ($h(q) < 0.5$) process of spot rates. A reason that mean-reversion was not found (dominant) is probably due to the use of high-frequency data which are not able to unfold the induced mean-reversion by shipping cycles occurring over longer time periods (Dixit and Pindyck,

1994). Adland et al. (2008) advanced strong support of mean-reversion of weekly spot earnings, rejecting the hypothesis that the price process is a Martingale (zero drift) at standard confidence levels at either end of the observed range of earnings. In addition, the speed of mean-reversion (i.e. the slope of the drift function) was found near constant.

As a means of benchmark, it is useful to make a short side-step and recalculate the Hurst exponent using the R/S method (see Edgar (1996) for a thorough overview) which is a simplified version of MF-DFA. The calculation can be summarized as:

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

In this classical compact form, σ_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 (Matos et al., 2004). 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 :

$$R/S(N) \sim N^H \quad (11)$$

By computing Eq. 10 and 11, the R/S analysis yields a Hurst exponent of 0.62 confirming the MF-DFA results. Moreover, the R/S method allows for a swift calculation of the time-dependent Hurst exponent $H(t)$. Especially in shipping where time is a crucial variable, calculating the time-dependent Hurst exponent is value added. 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 (Carbone et al., 2004). In figure 6, we have used a long enough and therefore reliable time window length of 1024. The selection of exactly 1024 observations is inspired by the technical details of the R/S method. Using a box size of 1024, the time series need not be broken into smaller blocks as 1024 or 2^{10} is an integer multiple of 2. As there are 4534 log-returns and the window starts progressing after 1024 observations, the analysis returns 4534-1024 or 3510 Hurst exponents. Figure 6 shows that $H(t)$ oscillates between ca. 0.64-0.74 supporting the controlled and smooth volatility of the freight rate increments.

Fig. 6. Time-dependent Hurst exponent $H(t)$.

Returning to MF-DFA, the analysis can be enriched by applying the different multifractal scaling exponents visualized in figure 7. The strong dependence between $h(q)$ or $D(q)$ compared to q surfaces that the price increments can be of multifractal nature. 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 α . Both the broad spectrum of $f(\alpha)$ and the rapid modified values of the Hölder exponent support multifractality.

Fig. 7. Multifractal scaling exponents $h(q)$, $\tau(q)$, $D(q)$ versus q (a,b,c), and derived α versus singularity spectrum $f(\alpha)$ (d).

In figure 8a, the origin of fractility can be detected, indicating that the multifractal nature of the price increments is mainly due to long-range effects rather than a fat tail. This holds both for the small and large variance regimes with respectively $q < 0$ and $q > 0$. The surrogate curve in the $h(q)$ panel is almost linear, strongly pointing to monofractality. The reason behind the strong presence of memory effects is probably the formation of spot rates itself. Everyday a brokerpanel consisting of 7 shipbroker 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. 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.

Figure 8b also allows to compare the multifractal spectra $\tau(q)$ of the original and randomized increments. It shows that the departure from the original $\tau(q)$ plot form is most striking for shuffled data, which also corroborates the findings from figure 8a.

Fig. 8. Comparison of scaling exponents $h(q)$ and $\tau(q)$ for original and randomized price increments.

The singularity spectrum in figure 9 provides another detailed test to track the types of multifractality. The reduced curvature of the shuffled (and surrogate) price increments clearly point that memory effects are present as the singularity strength $f(\alpha)$ of the higher values for the Hölder exponent α is destroyed. It is striking that especially for the higher values of the Hölder exponent the scaling or spectral behavior of the increments are destroyed by shuffling. This can be due to the fact that regions with high freight rates or volatility do not occur that often, so that shuffling quickly destroys this effect.

Fig. 9. Origins of the singularity spectrum.

For the sake of completeness we compare the obtained results with Goulielmos (2009) who calculated the α 's and Hurst exponents of Aframax tanker (80-120,000 deadweight ton capacity) freight rates from 292 monthly observations during 1984-2008. By so doing, an α of 1.56 or Hurst exponent of 0.64 ($H = 1/\alpha$) was found. Following Mandelbrot and Hudson (2004), α 's approaching 1.7 point to strong variations. As H is different from 0.5, the speed of the relevant time series was also different (in this case slower speed) than a random walk. Despite the fact that too few data were used to derive reliable Hurst exponents, the freight rate process, just as in our analysis, exhibited persistence or trend-reinforcement rather than mean-reversion behavior. Apart from this, the conclusion in Goulielmos (2009) is flawed as it is incorrect to link memory effects to the phenomenon of cycles in shipping. Cycles would much more bring forth the mean-reversion property in the data, something which both our and the analysis of Goulielmos does not confirm. This fact could possibly be linked to the use of high frequency data, that more easily track memory effects rather than mean-reversion.

6. Concluding remarks

In this paper we have applied multifractal methods to analyze the LPG spot freight rates for VLGCs. In line with maritime theory, spot rate changes demonstrate positive skewness and excess kurtosis. Given the lack of consensus on the stationarity of freight rates, it is beneficial that MF-DFA can overcome this issue. It is also welcomed that by definition both the dataset is detrended to e.g. counter seasonality influence and that nonlinearities are dealt with.

The different approaches used clearly indicated multifractal features of the freight rate process instead of a random walk. The log-log plot visualized the multifractal dimension and supports that different trend functions could be used to describe freight rate increments. The Hurst exponent of 0.67 and the time-dependent Hurst exponent of 0.64-0.74 computed via R/S analysis indicate that freight rates exhibit smooth trend behavior and persistence, underlining the controlled volatility and memory present in the time series. This trend in VLGC spot rates dominated the mean-reversion process or presence of a long-run equilibrium freight rate which is a characteristic inherent in shipping cycles. The reason for this can be due to the use of high frequency data.

By tracking the origin of multifractality, it was evidenced that both in the small and large variance segments long-range correlations or memory effects prevail rather than a fat tail in the PDF. Especially in dull markets with rates oscillating around operating costs can we evidence that freight rates are close to the previous rate reported. This explains the memory effect and the strong bearing of shuffling the increments in the small variance segments. As firm freight markets occur less frequently, shuffling quickly destroyed the memory effects in the high variance segments, which was articulated by the reduced curvature of the singularity spectrum.

The above findings provide a good measure of volatility and risk in the VLGC market, and pinpoint that multiscaling features should be taken up in freight rate models. This is among other things important when a profile of freight rate derivatives needs developing. Also for the finance industry, it is invaluable to characterize the spot rate process in order to better estimate the asset values of gas carriers. The fact that rates are trend-reinforcing could cater for profitable investment strategies. In order to do so, further research should deal with scrutinizing the properties of asset prices of VLGCs.

References

- Adland, R., Cullinane, K., 2006. The Non-linear Dynamics of Spot Freight Rates in Tanker Markets. *Transportation Research Part E: Logistics and Transportation Review* 42(3), 211-224.
- Adland, R., Haiying J., Lua, J., 2008. Price dynamics in the market for Liquid Petroleum Gas transport. *Energy Economics* 30(3), 818-828
- Beenstock, M., Vergottis, A., 1993. *Econometric Modelling of World Shipping*. Chapman & Hall, London, UK.
- Bera, A.K., Jarque, C.M., 1981. An Efficient Large-Sample Test for Normality of Observations and Regression Residuals. *Working papers in Econometrics*, vol. 40. Australian National University, Canberra.
- Carbone, A., Castelli, G., Stanley, H.E., 2004. Time-dependent Hurst exponent in financial time series. *Physica A* 344(2), 267-271.
- Damodar, N.G., 2003. *Basic Econometrics*. MC Graw Hill, New York.
- Dixit, A., Pindyck, R.S., 1994. *Investment Under Uncertainty*. Princeton University Press, New Jersey.
- Edgar, E.P., 1996. *Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility*, John Wiley and Sons, New York.
- Engelen, S., Dullaert, W., 2009. LORGAS – A Classical Partial Disequilibrium Model of the Gas Shipping Markets. Submitted to *Journal of Transport Economics and Policy*.
- Engelen, S., Dullaert, W., Vernimmen, B., 2007. Multi-agent adaptive systems in dry bulk markets. *Transportation Planning and Technology* 30(4), 377-389.
- Engelen, S., Meersman, H., Van de Voorde, E., 2006. Using system dynamics in maritime economics: an endogenous decision model for shipowners in the dry bulk sector. *Maritime Policy & Management* 33(2), 141-158.
- Fama, E., 1970. Efficient capital markets: a review of theory and empirical work. *Journal of Finance* 1970(25), 383-417.
- Feder, J., 1988. *Fractals*. Plenum, New York.

- Kantelhardt, J.W., Zschiegner, S.A., Bunde, E.K., Havlin, S., Bunde, A., Stanley, H.E., 2002. Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A* 316(4), 87-114.
- Glen, D., 2006. The modeling of dry bulk and tanker markets: a survey. *Maritime Policy & Management*, 33(5), 431-445.
- Goulielmos, A.M., 2009. Risk analysis of the Aframax freight market and of its newbuilding and second hand prices, 1976-2008 and 1984-2008. *International Journal of Shipping and Transport Logistics*. 1(1), 74-97.
- Haralambides, H.E., Tsolakis, S.D., Cridland, C., 2005. Econometric modelling of newbuilding and secondhand ship prices. In: Cullinane, K. (ed). *Shipping Economics*, Vol.12. Elsevier, London, p. 65-105.
- Hawdon, D., 1978. Tanker Freight Rates in the Short and Long Run. *Applied Economics* 10(3), 203-17.
- Jing, L., Marlow, P.B., Hui, W., 2008. An analysis of freight rate volatility in dry bulk shipping markets. *Maritime Policy & Management* 35(3), 237-251.
- Kavussanos, M.G., 1997. The dynamics of time-varying volatilities in different size second hand ship prices of the dry cargo sector. *Applied Economics* 29, 433-443.
- Kavussanos, M.G., Alizadeh, A., 2001. Seasonality patterns in the dry bulk shipping spot and time-charter rates. *Transportation Research – Part E; Logistics and Transportation Review* 37(6), 443-467.
- Kavussanos, M.G., Alizadeh, A., 2002. Efficient pricing of ships in the dry bulk sector of the shipping industry. *Maritime Policy and Management* 29, 303-330.
- Koekebakker, S., Adland, R., Sødal, S., 2006. Are spot rates stationary? *Journal of Transport Economics and Policy* 40(3), 449-472.
- Kulkarni, C.O., Vigneshwar, R., Jayaraman, K.V., Kulkarni, D.B., 2005. Identification of coding and non-coding sequences using local Hölder exponent formalism. *Bioinformatics* 21(20), 3818-3823.
- Lensberg, T., Rasmussen, H., 1992. *A stochastic Intertemporal Model of the Tanker Market*. Foundation for Research in Economics and Business Administration. Bergen, Norway.
- Mandelbrot, B.B. and Hudson, R.L., 2004. *The (mis)Behaviour of Markets: A fractal view of risk, ruin and reward*. Basic Books Inc., New York, USA.
- Mandelbrot, B.B. and Wallis, J.R., 1969. Robustness of the rescaled range r/s in the measurement of noncyclic long run statistical dependence. *Water Resources Research* 5(5), 967-988.
- Matos, J.M.O., Moura, E.P., Krüger, S.E., Rebello, J.M.A., 2004. Rescaled range analysis and detrended fluctuation analysis study of cast irons ultrasonic backscattered signals. *Chaos, Solutions & Fractals* 19(2), 55-60.
- Ossadnik, S.M., Buldyrev, S.B., Goldberger, A.L., Havlin, S., Mantegna, R.N., Peng, C.K., Simons, M., Stanley, H.E., 1994. Correlation approach to identify coding regions in DNA sequences. *Biophysical Journal* 67(1), 64-70.
- Panter, P.F., 1965. *Modulation, Noise and Spectral Analysis Applied to Information Transmission*. McGraw-Hill, New York.
- Peng, C.K., Buldyrev, S.V., Havlin, S., Simons, M., Stanley, H.E., Goldberger, A.L., 1994. Mosaic organization of DNA nucleotides. *Physical Review E* 49(2), 1685-1690.

Sadegh Movahed, M., Jafari, G.R., Ghasemi, F., Rahvar, S., Rahimi Tabar, M.R., 2006. Multifractal Detrended Fluctuation Analysis of Sunspot Time Series. *Journal of Statistical Mechanics: Theory and Experiment* 2006(2), P02003.

Stopford, M., 2008. *Maritime Economics*. Routledge, London.

Strandenes, S.P., 1984. Price determination in the time charter and second hand markets. Center for Applied Research, Norwegian School of Economics and Business Administration, Working Paper MU 06.

Strandenes, S.P., Adland, R., 2007. A discrete-time stochastic partial equilibrium model of the spot freight market. *Journal of Transport Economics and Policy* 41(2), 189-218.

Strandenes, S.P., Wergeland, T., 1982. *Freight Markets And Bulk Demand Efficiency*. Centre for Applied Research, Norwegian School of Economics and Business Administration, Bergen, Norway.

Taqqu, M.S., Teverovsky, V., Willinger, W., 1995. Estimators for long-range dependence: an empirical study. *Fractals* 3(1995), 785-798.

Theiler, J., Eubank, S., Longtin, A., Farmer, J.D., 1992. Detecting Nonlinear Structure in Time Series. *Physica D* 58(1992), 77-94.

Tinbergen, J., 1934. Tonnage and Freight. In: Klaasen, L. H., Koyck L. M., Wittenveen, H. J. (eds.), *Jan Tinbergen - Selected Papers*. North-Holland Publishing Company, 1959, Amsterdam.

Tvedt, J., 1997. Valuation of VLCCs under income uncertainty. *Maritime Policy and Management* 24(2), 159-174.

Tvedt, J., 2003. Shipping market models and the specification of freight rate processes. *Maritime Economics and Logistics* 5(4), 327-346.

Tvedt, J., 2003b. A new perspective on price dynamics of the dry bulk market. *Maritime Policy and Management* 30(3), 221-330.

Zannetos, Z.S., 1966. *The Theory of Oil Tankship Rates*. MIT Press, Cambridge, MA.