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Review

Long-term forecasting of BFI using chaos cycle theory and maritime technical analysis

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We tackle the problem to produce reliable *long-run* freight rates forecasts in maritime economy. Available tools developed in academia aimed at predicting stock prices with short term correlation, using models like GARCH. Moreover, Chaos theory models developed since 1963 by Mandelbrot, using Rescaled Range Analysis, provide short-run forecasts, the range of which depends on Lyapunov's exponent. Moreover, "Maritime" Technical Analysis, due to Hampton, supports the existence of short-run (3-4 years) and long-run (16-24 years) shipping cycles. So, the paper applies rescaled range analysis and maritime technical analysis to produce long-term forecasts through cycles. Since 1981, and in 1973, and at the end of 2008, shipping has experienced dramatic drops in freight markets, which Mandelbrot, in another context, described as the "joker" in the pack and "Noah" effect. Applying BDS and other tests on BPI time series of daily and weekly rates (1999-2011), we found: non-normality, long term correlation and chaos. The Hurst exponent found 0.93<1.00, indicating a very strong 'black' noise. The 'Lyapunov' exponent allowed forecasting up to 6 days/weeks. In such a case, to obtain long term forecasting we calculated cycles on the principle that those persistent cycles will be repeated. Cycles identified with Chaos theory were: 28 months to 35 and 4 to 9 years -using Vn statistic. In addition, Maritime technical analysis showed the short term cycle, which ended in May 2011, and the long term cycle, to end in 2017.

Keywords: forecasting freight rates index, chaos and Vn statistic/H exponent, maritime technical analysis, BPI 1999-2011, tests for normality (JB) and iid (BDS)

INTRODUCTION

The more volatile markets are, the more accurate forecasting is needed, especially if markets suffer from abrupt falls and rises, like Maritime. The evolution of the dry cargo index since 1741 is shown (Figure 1). Great spikes are shown in 1918 and in 2008. Stopford (2009) identified 22 cycles, 8 of which occurred after 1947. The 1918 spike is due to the heavy losses of ships due to First World War. The longer cycles, of 14 and 15 years, occurred in 1956 to 1969 and in 1988 to 2002. Last cycle ended in end 2008 and lasted 9 years since 2000.

In late 2008, one of the freight markets fell by 84% from 11 793 units on 20th May 2008 to 1 861 in August 2009. This great fall was not *anticipated* by ship-owners, academia or bankers. Moreover, the inability to foresee this last crisis, resulted, we believe, in over-placed orders, or overshooting, for new ships (Figure 2).

Between 2006 and 2008 more than 160 million dwt of Capes were ordered. This abrupt rise represents twice the number of immediate past orders (1996-2005). After 2007, the all period high (88 million dwt) of orders, fell by

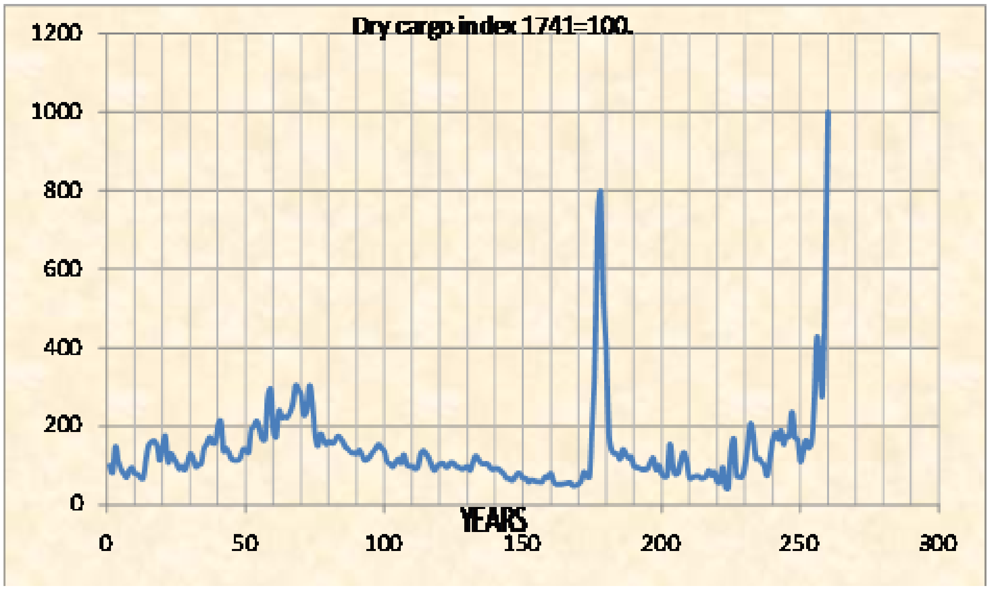

Figure 1. Maritime Economics Freight index, 1741-2008.

Source: Data from Stopford (2009). Also 1947=100.

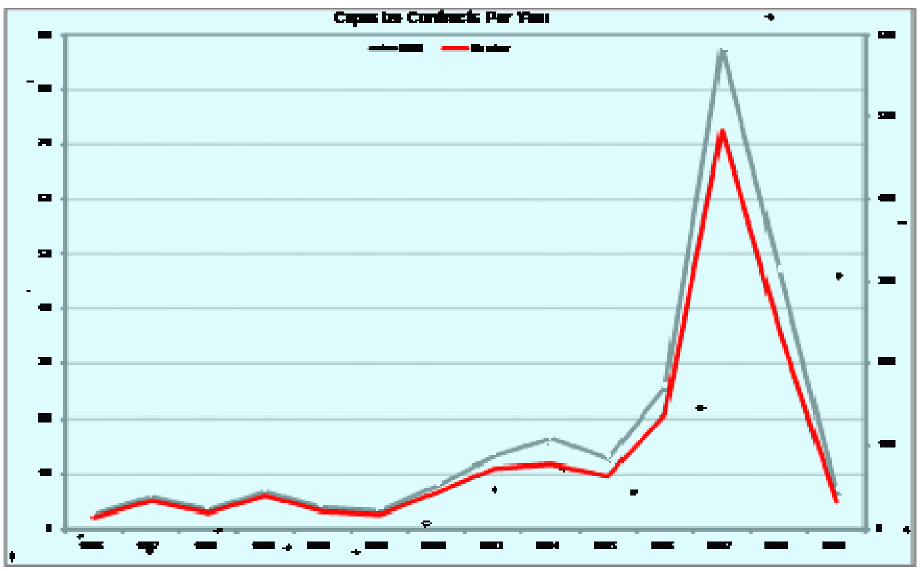

Figure 2. Ship building contracts placed each year for Capes (Bulk carriers sized usually over 100 000 dwt. In 2009 were from 170 000 to 180 000. They received their name from their inability to transit Panama Canal and to pass round the Cape of Good Hope),
1996-2009 (in Dwt and number of vessels).
Source: Data from Clarkson's; prepared by Dr M. Psifia.

46% in 2008 (48 million dwt), and to a low (8 million dwt) in 2009. While ordering is an action of optimism, delivery is an action of regret*,* if markets become depressed after ordering and during delivery. In 2011, 132 million dwt dry cargo ships delivered, in 2012 100 million, falling to 35 million in 2013 and 7 million in 2014 (Clarkson's data).

Entrepreneurs and ship-owners, from the start of the establishment of their companies, faced *business risk*; as a result efforts were paid to forecast future; academia tried to respond to this challenge. Figure 3 shows 4 schools available in academia to protect from risk. The first used, but also simple, method was '*Fundamental Analysis*' (Siriopoulos, 1999).

Fundamental analysis (FA) is based on the idea that a result always comes after a cause; if a stock price increases, then the cause is in the company, the industry or the economy. The price of a stock, bond, derivative or currency, moves because of some event, which, more

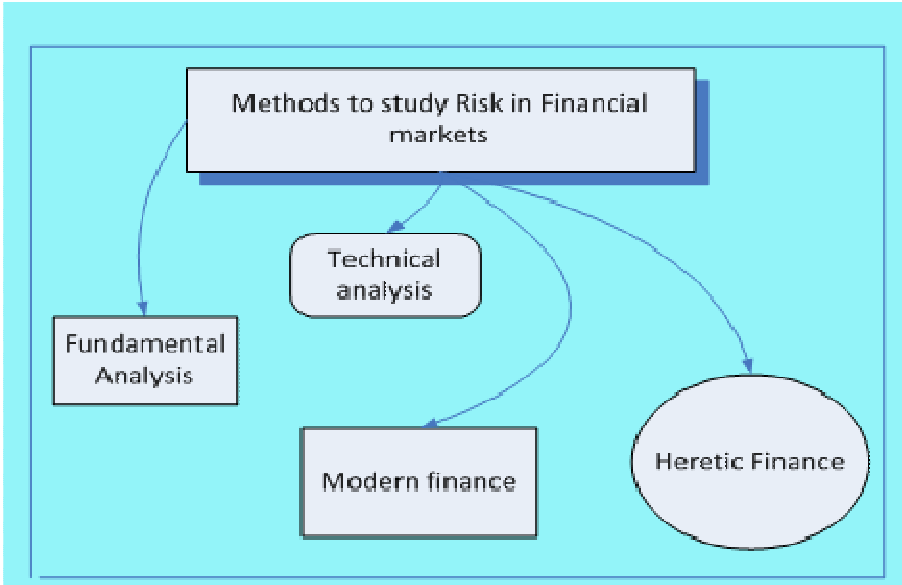

Figure 3. Methods of studying Risk in financial markets.
Source: Inspired by Mandelbrot and Hudson (2004), p. 7-13.

often, comes from outside market. Briefly, *if one knows the cause, one can forecast and manage risk.* FA tries to apply economic theory directly to the prediction of share prices, aided by mathematical/statistical and econometric models. Moreover, it aims at determining quantitatively the factors forming share prices and estimating equilibrium price (intrinsic value). It is argued that if the current price is greater than its intrinsic value, then price must fall, and vice versa.

FA is a simple method that cannot deal with complex reality, we believe. In real life, causes are obscure and critical information is unknown. Reasons are concealed and the connection between news and prices is inconsistent (Mandelbrot and Hudson, 2004).

Remaining methods shown in Figure 3 are presented below.

This paper applies 'maritime technical analysis'-MTA in forecasting short- and long- term weekly BPI (1999-2011) by identifying 2 major cycles. These cycles fit the past well so that to assume that they will persist also in future. Lyapunov exponent (This exponent, due to Russian Lyapunov, is used as a measure of the ability of a system to forecast for specific time steps ahead) on the other hand (Chaos theory) allowed forecasting maximum 6 days and/or 6 weeks outside the sample. This is not helpful. To overcome this, we used 'Chaos cycle theory' providing long-term cycles of 4-9 years.

Next, follows a literature review on general forecasting and maritime. Then, concepts from modern finance are reviewed. Next, heretic finance ('Heretic finance' is our term to distinguish it from 'modern finance'. Latter assumes normal distribution. It is formulated, the last 50 years, by Mandelbrot. Another basic difference of Heretic finance is the *long term dependence* found in time series) and chaotic time series are presented, being our theoretical basis. Then, 'poker' and 'joker' metaphors, in maritime businesses, are explained. Moreover, the paper applies nonlinear chaotic forecasting and nonperiodic cycles. Next, MTA is applied and forecasts are made. This is followed by conclusions.

Literature review

Economists, working on stock prices, assumed that the resulting price is the culmination of *purely random changes, as* argued by Mills (1999), Working (1960) and Cowles and Cowles and Jones (1933-1944; 1960). Cowles argued that there is little evidence that markets and financial analysts can predict future price changes. Kendall (1953) argued (British statistician, who took a long look at London shares, NY cotton and Chicago wheat, more than a century of data, in search of conventional patterns upon which an investor could turn an easy buck. 'On the whole', he laconically concluded after pages of fruitless regression analysis, 'I regard this experiment as a failure…There is no hope of being able to predict movements on the exchange') that the weekly changes of many financial prices *could not be predicted* from either past time series changes or from past changes in other price series. Roberts (1959) argued that price changes are *independent*. Osborne (1959) concluded that logarithmic price changes are *normally distributed, i.e.* follow 'random walk' (The term 'Random Walk' appeared first in a correspondence in *Nature* in 1905 between Pearson and Rayleigh) - (RW) and prices are generated by a 'Brownian motion' (This is 'the erratic movement of a small particle suspended in a fluid', seen by Robert Brown (a botanist) in 1828. This is due to water molecules colliding with this particle. Einstein (1905) proved rigorously the relationship between Brownian motion and random walk. Weiner in 1923 modeled Brownian motion as a random walk with an underlying Gaussian statistical structure (Feder, 1988; Peters, 1994)) - (BM).

In rigorous terms, RW is defined by Pt=Pt-1+et [1], where Pt is the observed price at a q given time and et is the independent error term with zero mean. Let a price change be: ΔPt = Pt-Pt-1 [2], with an independent error. Moreover: Pt= $\sum_{i=1}^{t} a_i$ [3], where i=1…t. Equation [1] is due to Osborne (1959) and applies to the logarithms of current prices with zero mean and constant variance, under normal distribution. Prices are *accumulations of purely random* changes.

Early RW works were collected by Cootner (1964) and developed in detail by Granger and Morgenstern (1970). Historically, the doctoral thesis of Bachelier (1900) followed random walk. He developed many of the mathematical properties of 'Brownian motion', five years earlier than Einstein (Einstein A, (1905), Uber die von der molekularkinetischsen theorie der warme geforderte bewegung von in ruhenden flussigkeiten suspendierten teilchen, *Annals of Physics*, 322). Einstein was the one to prove RW by this equation: distance=$\sqrt{time}$. The RW model can be tested by the autocorrelation properties of price changes (Fama, 1965), viewing equation [1] as a "model of an ARIMA (ARIMA='Autoregressive-integrated-moving average' process, i.e. a *non-stationary* stochastic process related to ARMA. It becomes stationary if differenced d times, where d=integer. ARMA=*stationary* stochastic process mixed with AR and MA (moving average) processes. AR=a *stationary* stochastic process, where the current value of time series is related to its past p values (p=an integer); if p=1, we have AR(1) with infinite variance; if p=2, we have AR(2), related to previous 2 values. Small (2005, p. 172) noted that his data of financial time series exhibited deterministic components, which, however, are *assumed* by ARIMA and GARCH to be stochastic) process" (Box and Jenkins, 1976), (i.e. as an uni-variable *linear* stochastic process).

Other approaches (One may distinguish between 'integrated' and 'non-integrated' time series. In maritime economy it is assumed that one variable causes another variable; thus co-integration is a commonly tested hypothesis in shipping modeling) use also 'linear stochastic models' to determine the 'order of integration'. Moreover, replacing RW hypothesis with 'martingale (It rules out the dependence of the conditional expectations of changes in future values on the information available today)', we can use ARCH (ARCH= the first-order 'autoregressive conditional heteroskedastic' process. This is *very popular* dealing with financial time series. However, it requires 'conditional variance' (σ^2) to be always positive. 'Autoregressive conditional' means that the changes in variability are controlled by data's past behavior. The variance is time-varying and conditional on past one. It exhibits frequency distributions with *high peaks at the mean and fat-tails)* model (Engle, 1982). The modeling of integrated (financial) time series is in particular very popular among maritime economists. To test for co-integration and carry out estimation, the 'vector error correction model'-VECM (VARs containing integrated and co-integrated variables enable to develop the VECM framework) is used.

Forecasting *maritime* markets, despite its high importance (Stopford, 2009), accounts for few works. Tsolakis et al (2003) presented a model to forecast second hand ship prices (1999-2001), using AR, Xt+1=μ+ρXt+η_{t+1}, where μ is the mean, η is a shock at t, ρ the autoregressive coefficient and X=second hand prices. They compared their (inside the sample) forecasts (not written down) with the above equation with a structured ECM, by calculating mean squared, absolute and % error. They found that the two models shared success among *two different classes of ships*: AR/VAR (VAR=Vector AR) performed better in bulk carriers (handy, Panamax, Cape; handy tankers) and SEM performed better in larger tankers (Panamax, Aframax, Suezmax and VLCC), but they gave no explanation why. They argued that SEM is good to describe and forecast cycles and to evaluate policies, while VAR is good for other purposes…

Batchelor et al (2007) tested (The results are questionable due to significant serial correlation, heteroskedasticity, excess kurtosis in all series; also excess skewness in most; Jarque-Bera found departure from normality in all routes for both spots and futures…) the performance of ARIMA and VECM models in predicting spot and forward freight rates (Table 1):

Forecasting freight rate markets, using *non-linear* regression methods, appeared first in 1997 (McConville and Rickaby (1995) found, out of 1750 authors, 9 having studied forecasting demand between 1983 and 1993, and 12 forecasting 'international trade', between 1971 and 1993, including MSc and PhD theses and studies by organizations etc. None used nonlinear techniques in these 21 studies. Among the topics were: expectations (Wright: 1993), autoregressive modeling (1983), a PhD (1981) at the University of Liverpool for forecasting charter rates and Hampton's 3rd edition of his monograph (1991)) (Li and Parsons), using a nonlinear regression 'artificial neural network' model (1986-1993). Indeed, considerable attention has been paid in developing non-linear regression mathematical models (1986-1993). Li and Parsons (1997) used monthly tanker freight rates (1980-1995). Unfortunately, their results were mixed over the duration of forecasts: for one month neural networks were either *worse* than or *equivalent* with ARMA; for five

Table 1. Results of forecasting spot and forward freight rates, using ARIMA and VECM.

Model	**Evaluation one**	**Evaluation two**	**Results**
General VECM and restricted one plus SURE Forecasting 10 and 20 steps ahead.	Best in-sample fit, based on root RMSE. Using natural logs. Stationarity exists (tested by ADF, Phillips-Peron and KPSS 1992 tests).	*Future rates converge strongly* to spots. Futures are more *volatile* than spots and *harder to forecast*. Out of sample, *ECM fails to predict future rates,* but *spots* market is efficient.	Out of sample all models *outperform Random Walk*. Future rates *do help* to forecast spots. *Restricted VECM* outperforms RW.
VECM (VECM forecasting implies danger, if underlying market structure is evolving…as being not robust to structural change)	Unhelpful to predict future rates. Spots and future rates co-integrate.	*ARIMA or VAR* (Sims, 1980) forecast better. ARIMA less accurate than RW. VAR more accurate than ARIMA.	VECM, S-VECM, perform better than VAR in spots, but not in futures. S-VECM outperforms RW.

Source: Batchelor et al (2007).

months ARMA was *worse*; for 12 months ARMA was *better*, and for 24 months ARMA was *equivalent*.

Lyridis et al (2004) forecast VLCC spot rates (1979-2002) using also neural networks, believing that those are more suitable for shipping *non-stationary non-linear time series*. Their forecasts, though better than those of Li and Parsons (1997), showed deviations from actual values varying by between 30 and 60 world-scale units for 1 month to 12 months ahead.

Chaotic (It is the case when we have a stochastic behavior appearing in deterministic systems (Royal statistical society, 1986 conference, UK). Chaos has the properties of sensitivity on starting conditions and the existence of an attractor. It is defined below in more detail) methods applied also to maritime forecasting (Goulielmos and Psifia, 2009; Goulielmos, 2009; 2010; 2011; Thalassinos et al*,* 2009). The first forecast the 'one year weekly time charter of a 65 000 dwt bulk-carrier' (1989-2008), using the nonlinear methods of 'principal components' and 'kernel density estimation'-KDE. Forecasts outside the sample, compared with published values (Due to retarded publication), varied from $28 per week to $623, i.e. 0.97% on a total of about a $60 000.

Moreover, Goulielmos (2009, p. 345) used 543 values of the BPI to predict 6 weeks ahead using the nonlinear methods of Ordinary Least Squares and KDE. The deviations inside the sample varied from 2.26% to 16.31% (i.e. $979) on about a $6 000 weekly freight rate (26/08/2008- 29/09/2008). The prediction for September 29th, 2008, was $2 839 against an actual value of $2 376, which he took them as an indication that the end 2008 crisis was coming, compared with $4 885 a week before. Moreover, Goulielmos (2010) used historic data of second hand ship prices to predict for next 12 months. Three nonlinear methods applied simultaneously. He achieved deviations of less than 1% inside the sample. Predicted prices varied from an absolute $64.50 million to $70.50 (2006-2007) and differed from actual values (published figures) from $64.40 to $ 70.82.

Thalassinos et al (2009) predicted Aframax tanker rates (105,000 dwt double hull) on a 401 weekly charter rate index, using 'False Nearest Neighbors' method for 30 steps ahead (03/2000-11/2007). Their deviations were from $4.20 to $1 789.20 per week for k=10, 20 time steps on about $33 000 absolute actual and $1 737 for k=30 and a relative error about 5.11% maximum. Predictions on absolute amounts deviated almost twice from actual compared with those of Goulielmos (2009).

Concluding, we see that general economists using random walk models were disappointed in their efforts to forecast real stock prices or their changes. It is true, however, that they tried to respond to the shortcomings appeared and provided econometric solutions after AR model (Yule, 1927), with such models like ARMA, ARIMA and GARCH. GARCH in fact faced the shortcomings of previous models and indirectly admitted them. Important is the conditional variance adopted. Maritime economists by following general economists applied their models, especially GARCH, to maritime economy with a 10-year delay.

The maritime cases, reviewed above, ended in mixed results or rejected random walk or forecast serious deviations from real freight rates. Nonlinear chaotic models testing for long term dependence (Hurst exponent), non-periodic cycles ('Joseph' effect) and catastrophic changes in freight markets ('Noah' effect) outperformed GARCH and are considered more suitable than artificial neural networks (Goulielmos et al, 2012).

Concepts in modern finance reviewed

Modern finance is based on the mathematics of chance and on statistics, accepting that prices are unpredictable, though their fluctuations obey the mathematical laws of chance. As a result risk is measurable and manageable. The main work started in 1900 with the doctoral thesis of the mathematician Bachelier, who studied financial

Table 2. Years that freight rates went out of 3 standard deviations, 1914-2008.

YEAR	DEVIATION FROM THE MEAN (in σ)
1914	4.57
1920	3.45
1960	3.08
1970	-3.28
1972	4.96
1973	-4.88 and 7.04
1974	4.00 and – 3.55
2004	5.23
2008	-9.56

markets. He drew upon Pascal (Blaise Pascal (1623-1662), a French mathematician) and Fermat (Similarly, Pier De Fermat, 1601-1665) (1654), inventors of probability theory. Bachelier (1900) established RW model, which postulates that *prices will go up or down with equal probability; their variation is measurable.* Most changes fit the bell shape histogram; 68% of moves are small and within one standard deviation from the mean; 95% are within 2σ and 98% within 3σ. *Extremely few* of the changes are very large. The numerous small changes cluster in the center of the bell; the rare big changes are indicated by the tails of the distribution. Mathematicians called this bell curve 'normal' and it was first described by Gauss (Carl Friedrich Gauss in his book: 'A Theory of the movements of celestial bodies', 1809) in 1809.

As shown (in Goulielmos et al, 2010), the dry cargo index of freight rates, between 1914 and 2008, deviated by more than 3 standard deviations on 11 occasions (Table 2):

As shown, large changes are much more common than suggested by Bell curve, and the probability for that is no greater than 2%. The Noah effect has appeared in our times in 1973, in the form of energy crises, and in end 2008, in the form of the banking crisis.

A more general statement of Bachelier's thinking goes by the 'efficient market hypothesis' (Fama, 1991). This means that in an ideal market, all relevant information is already priced into a security *today*. Yesterday's change does not influence todays, nor todays, tomorrows, and each price change is independent from the last.

Bachelier's model adopted 2 critical assumptions: price changes are statistically independent and are normally distributed. This, however, confronted reality, especially during the 1990s. Many (Mandelbrot and Hudson (2004, p. 12)) financial price series have a memory; today does in fact influence tomorrow. Large changes in prices today are likely to be followed by large changes next day, and the reverse is also true. There is no well-behaved, predictable, pattern in prices, or a periodic up-and-down procession from boom to bust in business cycles. There is a long term memory, and price time series have different degrees of memory. This, unfortunately, made the RW model inapplicable.

Heretic Finance and tests

(1) To deal with maritime time series, it is necessary to make certain tests.

(a) Maritime time series is assumed to follow financial ones (Jing et al, 2008; Chen et al, 2010) – i.e. to be *non-stationary*. To transform them into stationary, we applied a filter (the *first logarithmic differences)* [Peters (1994)].

(b) Financial time series are unfailingly tested for *normality*. If variance is time-varying as assumed by GARCH, then management of risk is different from when variance is constant. In our case, we calculated the Jarque-Bera-JB test of normality (Kurtosis on non-stationary data for BPI for 2815 daily time charter rates is 1.670856 and skewness is 1.404267. JB= (2815/6)1.404267+ (2815/24)). The JB was found to be equal to 866 (rounded) > 5.99 for a=5% for 2 degrees of freedom. Data, therefore, are not normally distributed. This conclusion is in line with previous research (e.g. Goulielmos, 2010). Moreover, all maritime economists in their models have found such anomalies like excess kurtosis and excess skewness (Goulielmos, 2012).

(c) *BDS test*. This is a test of statistical independence, which indicates whether there are in the data 'nonlinear dependencies'. This will tell us whether our data can be described by a nonlinear model. The test is done using the BDS (This is due to Brock, Hsieh and Le Baron, (1991)) statistic. This is a powerful test to find out whether the iid hypothesis stands in a linear, chaotic or stochastic nonlinear model. Running this test with MATLAB 7.9, we derived four values of the BDS for embedding dimensions/correlation dimensions 2, 3, 4, and 5 with e/σ=1.5 (suitable for low dimensions, as in our case), where σ is the standard deviation of a normally distributed sample, and e=the dimensional distance. The values are: 10.0113, 11.8654, 13.1226 and 13.8816. For a sample size n=500 (near our sample of n=573), the critical values with 99.5% confidence level are: 2.80, 2.86, 2.86 and 2.94 from the table due to Kanzler (1999). Consequently BPI time series *are not iid*.

(d) *Efficient market hypothesis*. This hypothesis states that all available information is directly and fully reflected in prices. Both Samuelson (1965) and Mandelbrot (1966) have demonstrated that *if* transaction cost is zero and *if* investors have easy access to the quickly diffused information, then we may use a RW model. Fama (1965) classified market efficiency in three levels: weak, strong and semi-strong. Moreover, Fama (1991), and other financial analysts, argued that returns are characterized by short-term memory or there is a short-term autocorrelation. To test the existence of a memory, and its length, we used 'Rescaled Range Analysis'-RRA, first described by Hurst (1951) and then by Mandelbrot (1972), Greene and Fielitz (1977), Feder (1988), Peters (1994) and Steeb (2008).

(e) *Memory test*. Einstein (1905) proved that RW model obeys (This law expresses the situation where distance, covered by a random particle, undergoing random collisions from all sides, is directly related to the square root of time. Time in time series coincides with n, the number of time steps/observations. So, the square root of time is the square root of n) equation R=$\mathbf{T}^{1/2}$ [1], as mentioned, where R is the distance covered by a particle, and T the time index. Hurst (1951) proposed a more general one (Mandelbrot and Hudson, 2004; Peters, 1994; Steeb, 2008), which can be applied to a broader class of time series, including RW: R/S=k$\mathbf{T}^{\mathbf{H}}$ [2]. Where R/S is the rescaled range (This is a dimensionless ratio (Steeb, 2008) that scales by H as time increases. Rescaling permits the comparison of distant observations, and it can be used for time series with no characteristic scale. It obeys 'fractal geometry'. This is the branch of geometry invented and elaborated by Mandelbrot (1951-1977)) [i.e. the range = maximum less minimum value of time series divided by (local) standard deviation], T is the index for the number of observations n/or for time, k is a constant and H is the Hurst exponent, a power law, where 0≤H≤1. *If H=1/2* then series is independent and follows RW/White noise/BM.

Moreover, BM can be generalized into the 'fractal (Fractal is the object that is similar to a larger object of which is a part. E.g. the branches and their tree. This property is called self-similarity. Time series are self-similar under scale) Brownian motion' (FBM) using formula [2]. Here H (We have applied Hurst process on *first differences* as a test (Mandelbrot, 1972) to avoid taking values of H near 1; no differences noted when used *first logarithmic differences* (Peters, 1994)) found 0.93 (rounded) at n≥14 on 2815 daily time charter rates for BPI (1999-2011) using the computer program NLTSA V.2.0 (2000) using formula log(R/S) =log (k) + H log (T) [3]. This is equation [2] by taking logs. The value of H (H gives further information about BPI (1999-2011): (a) the fractal dimension of the *probability space* is FD=1/H= 1/0.93=1.075 (rounded) <2 (2=RW), (b) the fractal dimension in general equals FDTS=2-H=2-0.93=1.075, which is <1.50, (c) the rate of decay of the Fourier series is equal to RDFS=2H+1=0.93*2+1=2.86. This is denoted by 1/$f^{(2H+1)=2.86}$. The autocorrelation function (measuring the covariance of a data series with itself) at a time lag τ, is defined, for fractional Gaussian noise process H≠1/2 and large τ, as follows: $\boxed{\lim_{\tau \to \infty} C(\tau) \propto \tau^{2H-2}}$ [4] or $\boxed{\tau^{-0.14}}$. A random walk requires C (τ) = 0 (except for τ=0). This indicates *long term memory effects* and positive correlations for H>1/2 (=persistence). Mandelbrot, Taqqu and Wallis (1969, 1979) showed the power of the nonparametric RRA for determining long run dependence, even when time series are not Gaussian and exhibit excess kurtosis and excess skewness, as this is common in maritime time series (Jing *et al*., 2008). (d) the relationship between H and d (integration coefficient) in ARFIMA (fractional ARIMA) models: d=H-1/2; if 0<d<1/2, then ARFIMA process is *stationary and possesses long term memory* as in here, where d=0.93-0.50=0.43 <0.50) shows black noise (The characteristics of a time series: (a) to follow trends, (b) to have memory and (c) to have observations correlated, no matter how distant is one from the other. Hurst analyzed almost 850 years of data concerning Nile's water behavior) in the series and a speed higher than that of RW. Moreover, there is a 93% probability that the series will increase in the next immediately following period (2011+) (H indicates the 'Joseph' effect defined by Mandelbrot and Hudson, 2004).

As shown (Figures 4 and 7), the series has the potential of sudden catastrophes (called Noah effect defined by Mandelbrot and Hudson, 2004; Goulielmos, 2012). This series is not distributed independently, but is biased, as shown by H. This bias is due to the reactions of ship-owners in the current market conditions, using the information about current order book and delivery of ships released by shipping statistical houses and shipyards.

In appendix 1, we show the analysis we have followed to test whether data follows a deterministic law under a low dimensional chaos.

Maritime forecasting: A 'Poker' or a 'Joker' in the pack?

Stopford (2009, p. 700, 738-742) argues that 'Shipping investor are in much the same position as a … 'poker-player' trying to make an educated guess about opponent's cards. He recommends 'guessing' on 'best information'. For us, maritime forecasting is possible, if one realizes that it is not a 'poker' game, but a game involving a Noah effect" (Goulielmos, 2012). The

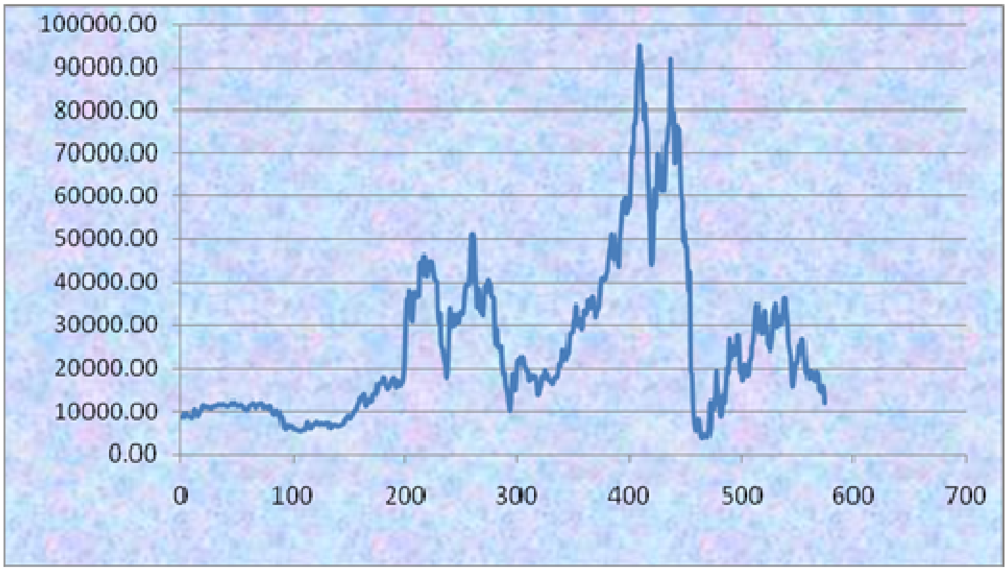

Figure 4. BPI per week, 1999-2011, 573 weeks.
Source: Data and excel; transforming 2815 days into weeks.

appearance of Joker coincides with the event of 'Noah effect' (Mandelbrot and Hudson, 2004) and latest research (Goulielmos, 2012) shows that it can be forecast.

To describe the situation with a joker (Peters, 1994), we will reproduce Hurst's (1951) process. Hurst simulated a random process using a deck of 52 cards containing numbers: ±1, ±3, ±5, ±7 and ±9. The deck repeatedly cut and shuffled. The number of the card appearing in each cut is written down and a sequence of 1000 cuts was recorded. *They followed RW…*

Hurst interested to see whether the whole process was a biased RW, as his data have shown (applying 'RRA' (A method developed by Hurst (1951) to determine long-memory effects and fractional Brownian motion)). To simulate that, he shuffled the deck and cut it once, noting the number (say +3). He replaced this card, reshuffled and created two decks of 26 cards (deck A and B). Then he took out the 3 highest cards from A and placed them into B; he also removed the 3 lowest cards from B. By this method he created a bias of +3 in deck B. He also placed a joker in B and reshuffled. Deck B now is a *biased time series generator*, and used it until the joker was cut, where upon the pack is re-biased. Hurst tried 1000 trials of 100 hands. *Time series then showed persistent RW.* The cuts of the deck were random, the generation of time series was also random and the appearance of the joker was random, *but still series showed persistence (*A rise yesterday gives a probability for a rise next day, and vice versa. This is attributed to the memory existing in the series, which is long and called 'black noise'. This memory establishes long term correlation/dependence) *…*

It seems that the trends of time series persist until an economic equivalent of joker arises to change persistence in magnitude or in direction or in both (Mandelbrot and Hudson, 2004; Peters, 1994; Steeb, 2008). Latest research (Goulielmos, 2012) has shown that a solution in the problem of predicting the 'Noah effect' is to predict alpha –the risk coefficient. Alpha is equal to 1/H, where H (the Hurst exponent) (Mandelbrot and Hudson, 2004).

Long-run forecasting

To overcome the very short-term forecasting, mentioned above, of six days, using Chaos theory, we have three options: (1) to transform daily data into weeks, where by so doing we extend forecasting period, (2) to calculate chaotic cycles and (3) to apply MTA.

(1) By turning daily data into weeks, we obtained Figure 4, which is self similar with Figure 7 (Another definition for fractality: Frequency distributions are self similar, if, after an adjustment for scale, have much the same shape (Peters, 1994).

In weeks the degree of persistence reduced, as expected, from H_1=0.93 to H_2=0.735, for n≥10 and n=574-1 weeks. Following the same steps, as in appendix 1, we found 'system's dimension' equal to 1.22 at 12 embedding dimension. The dimension is fractal, i.e. less than 2, and low. The weekly Lyapunov exponent, λ_2 equals 0.1709 at 97.3% R^2. The prediction period is (1/0.1709=5.85~) 6 weeks. This remains short. We turn now to the second option.

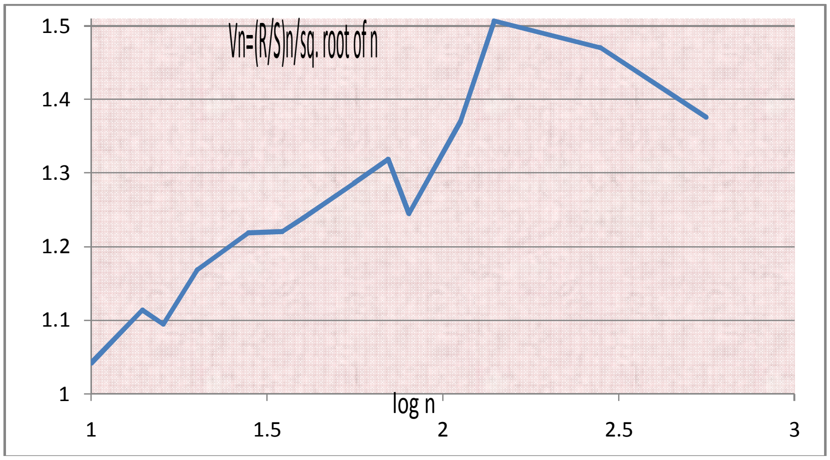

Figure 5. Vn versus log n for BPI 1999-2011 (weekly rates).
Source: Excel and NLTSA.

Table 3. Shipping cycles found by research, 2006-2012.

Duration	Duration (*)	Duration (**)	Duration (***)
35 months (****)	28 months (1)	32 months (4)	7 years and 8 years
6, 12, 30 years (****)	5 years (2)	4 years (5)	7.8 years mean
6 and 129 years (****)	8 years, 9 months (3)	8 years (6)	9 years plus

Source: (*) My student Mrs Psifia E-M in her PhD at the end of 2006 at the University of Piraeus, (available from my e-mail) found 1,2,3 cycles for the 'dry cargo charter index per trip', 1968-2003.(**) For dry cargo time charters 1971-2003, there was one cycle (4). For the dry cargo per trip charter, 1971-2003, there were 2 cycles (5, 6). (***) Stopford (2009) found a cycle of 7 years supported by statistics. (****) This paper.

(2) Nonperiodic chaotic shipping cycles

To find cycles, we divided (Data has to be divided into A groups of N length, where A*N is not necessarily to be equal to n but to be as close as possible to it. The rule is A each time to be divided exactly) weekly data of n=572 into 14 groups so that N times A is equal or close to n. This is the usual procedure with RRA (Peters, 1994; Mandelbrot and Hudson, 2004). We chose N=560 (leaving out 72 observations from the end) and found 14 integer dividers that divide N exactly, as they should. The method to calculate accurately the duration of cycles, [Peters (1994)], is by equation $Vn=R/S/\sqrt{n}$ (Figure 5) (RRA).

A cycle exists when Vn curve 'flattens out' (Peters, 1994, p. 92-93). The Vn statistic shows (At 4 months; at about 9 months, and at 20 months) (Figure 5) clearly 4 cycles (1999-2011). We single out the cycle that fits theory, which is that of 140 weeks (35 months) (Data's period (about 12 years) does not allow us to identify the 20-year's cycle proclaimed by theory (this limitation has been identified also in other maritime papers)). In many occasions the longevity of data led to wrong forecasts.

What if the long (1741-2008 is the full Stopford data period with missing figures for 8 War years) time series of the dry cargo index due to Stopford (2009), i.e. 61 years from 1941 to 2007, is used? H3 was 0.64 at n≥10 and 3 cycles appeared: 6, 12 and 30 years. Moreover, for the 259 years of Stopford's whole index, H4 was equal to 0.696 at n≥10 and 2 cycles appeared of 6 and 129 years respectively. We note that the cycle of six years appears in both time series.

It is worth noting that it was Chaos theory which has established the existence of nonperiodic cycles (unlike Fourier theory). On the past, the belief in the *regular* maritime cycles in its ups and downs (2-3 years up and 2-3 years down, as described by Stopford, 2009) has led in dramatic investment mistakes (notably that of Japanese 'Sanko Shipping' during 1981-87 crisis). These results indicate that shipping cycles differ from period to period and from index to index. The positive element, however, is that certain cycle durations appear *persistently* from a set of data to the other (Table 3). This is unlikely to be due to a mere chance.

We summarize the findings for cycles so far (Table 3).

Given the overlapping shown above, we may conclude that cycles appeared in maritime economy were from 28 to 35 months and from 4 to 9 years. We use this information to say that long term future cycle will be within this range, i.e. it will last from 2015 to 2020.

We turn now to the third option.

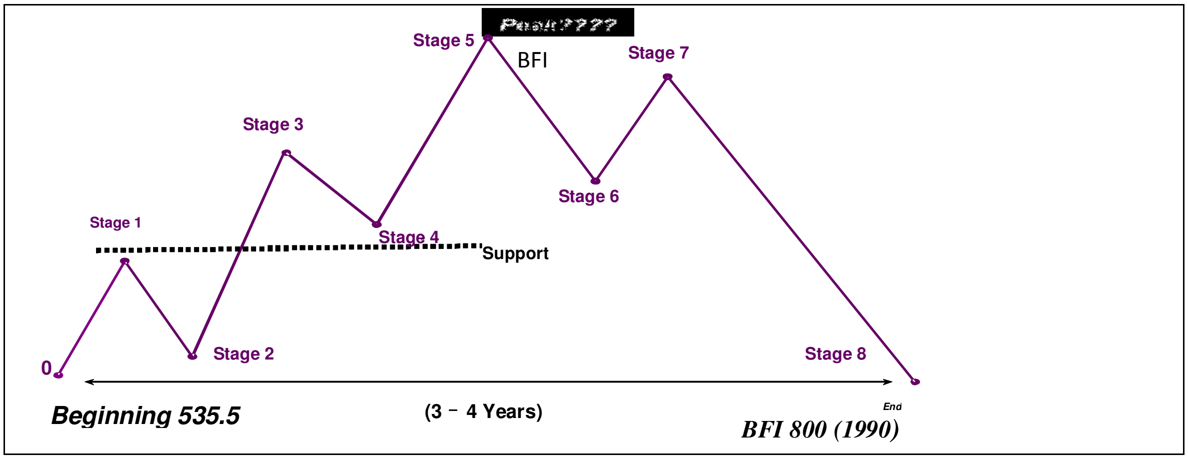

Figure 6. The 8 idealized stages of the short 3-4 years shipping Cycle, 1986-1990
Source: based on Hampton (1990).

Technical analysis (1930)

Technical analysis (TA) is used to recognize patterns, real or spurious, in studying large quantities of data on prices, volumes, and on indicators-charts in search of clues to buy or sell. TA expanded in 1990s, and appeared also on the internet, where stocks were traded. All major Forex (currency) houses use this analysis, and try to find support points and trading ranges (Mandelbrot and Hudson, 2004, p.8-9). Chartists *can at times be correct* and their models *may work…*(Mandelbrot and Hudson, 2004, p. 9). Maritime economy confirms this conclusion.

For Miner (1999, p. 2-3), the objective of TA is: "To identify those market conditions and specific trading strategies that have a high probability of success". The basic assumption of TA (Siriopolos, 1999; Miner, 1999) is that the *price level is determined by demand and supply*. In addition, past price time series shape the future levels of prices. There are two phases: an *accumulation* of shares, when prices are low and a *distribution* of them, when prices are high.

TA passed through 3 historical developments: (a) the Dow Theory (1902, 1922 and 1932), (b) the Elliott theory of waves (1930 onwards) and (c) the use of technical indices (1975 onwards). The second development is that which has influenced shipping (Frost and Prechter, 1978) and followed by Hampton (1990), and as a result we will focus on that.

Elliott in 1930 (Prechter, 1980), argued that markets follow 8 (*steady in number*) full waves with a repeated (impulsive) formulation of *5 waves up,* moving by a trend; also *3 corrective waves down (*Numbers 5 and 3 (of Elliott) follow the series of Arabic numbers introduced first in Italy by Fibonacci (Leonardo of Pisa, 1180-1250) in his book 'Abacus' in 1202. The Fibonacci series 1,1,2,3,5,8,13,21,34,55,89,144,233 are related to the 'golden ratio' or the 'spiral logarithm' of Ancient Greeks; this was known by Pythagoras; solving: $x^2 - x - 1 = F = 1{,}618,\ we\ derive$ the 'golden mean or divine proportion' or 'golden square'). Hampton took 8 stages in his short cycle. The waves are followed by 34 medium waves and 144 small waves (The 5 waves up create 21 waves (5+3+5+3+5), while the 3 ones down create 13 waves (5+3+5)). Important is that all numbers obey the '*Fibonacci*' series. Fibonacci (1175-1240) invented a series of numbers An, where A1=0, A2=1 and An=An-1+An-2, for every n>2. Waves in a time series obey this series as far as their duration and sequence are concerned.

Peters (1994, p. 43) argued that charts are important tools for the day traders in all trading rooms and for short-term investors. TA is based on the belief that there are regular market cycles, hidden by noise or irregular perturbations, that drive market's underlying clockwork mechanism. The information used is only related to the momentum of a particular variable and to market dynamics and crowd behavior.

Maritime technical analysis (1990)

Hampton (1990) argued that it is possible to make accurate short- and long-term forecasts of freight rates by combining market psychology with cycles of various durations. He singled out two major cycles.

(a) The Short-run Hampton's cycle (2002-2008)

The short run idealized cycle of Hampton, consisting of 4 shorter cycles and 8 stages, is shown in a historical picture in Figure 6 for 1986-1990.

This cycle, lasting 3-4 years, had 8 stages starting at stage 0 with 535.5 units in the BFI index in 1986. Up to stage 5 the freight rate shows 3 regular ups and 3 downs with the characteristic being the peak at stage 5 (1684

Figure 7. Panamax, 4 time charter routes of BPI $ per day, 01/11/99-25/01/11, 2815 days Source: Excel and data for BPI.

Table 4. Hampton's short cycle 3-4 years, 2005-2008

The General picture 01/08/2005 $1522 at the start, stage 0	Start 23/01/06, stage 1 at $ 1882	Stage 4 at $5472 11/06/07	Stage 7 at $11056 19/05/08- lower than that of stage 5 as in theory
13/10/2008 $1584 end, stage 8;	Stage 2 at $3632 23/10/06	Stage 5 (peak) at $11524 29/10/07	Stage 8 at $1584 13/10/08 –this should be equal to $1522 of stage 0;
The Detailed picture Start 01/08/2005 at $1522, stage 0	Stage 3 at $6261 14/05/07 - support from supply and demand equilibrium	Stage 6 at $5620 28/01/08	Duration 40.5 months (within theory of 36-48 months)

units). Stage 7 must be lower than stage 5 and stage 8 must be equal to stage 0 (800 units>535.5).

Next is a more contemporary picture of the short-run Hampton cycles (Figure 7): one from November 2002 to July 2005 (33 months from low to low; lasting 40.5 months<48 months maximum); one between 2005 and 2008 and one starting on 16th December 2008 and terminated in April 2011. Figure 7 above covers daily BPI from 01/11/1999 to 25/01/2011.

The cycles that can be read from Figure 7 are 2 finished and one on the way, from low to low: i.e. one from day 760 to day 1430, i.e. 22 months and 10 days; one from 1430 to 2240, i.e. 27 months and one from 2240 to 2815, i.e. 19 months and 5 days (which continued).

We see that cycles *last longer* as we move into the end 2008 crisis. The total duration is 7 years and about 4 months for the 3 short cycles since 2002, taking into account Hampton's theory. The lowest value of the index occurred on 12/12/08 at $3 537 (2 months later than theory).

Table 4 shows the freight rates that were formed during Hampton's short cycle (2005-2008).

Figure 7 shows that a new short cycle started on 13/12/08 at $3 537 plus (after the 2286th day) (This cycle started and continued beyond Jan. 2011). This is the correction phase. The *correction phase* is when excesses and mistakes in the build-up phase are corrected. According to Hampton (1990), the freight market during this phase is irregular; the first short cycle after crisis 2008-2012, as shown in Figures 4 and 8, produced lower (<$30 000) freight rates. Ordering new ships ceased, apart for speculation and 'false dawns' ('False dawn' is a metaphor meaning that ship-owners proceed to get finance from their bankers believing on the coming of a 'dawn', i.e. a permanent improvement of freight market, which, however, proves to be deceptive. A barometer of the market to improve is the minimal amount of laid up tonnage).

Crisis has cropped the upper high level of daily time charters (which were as high as $96 000). The 2008-2012 cycle produced $3 500 (The chart (Figure 8) shows

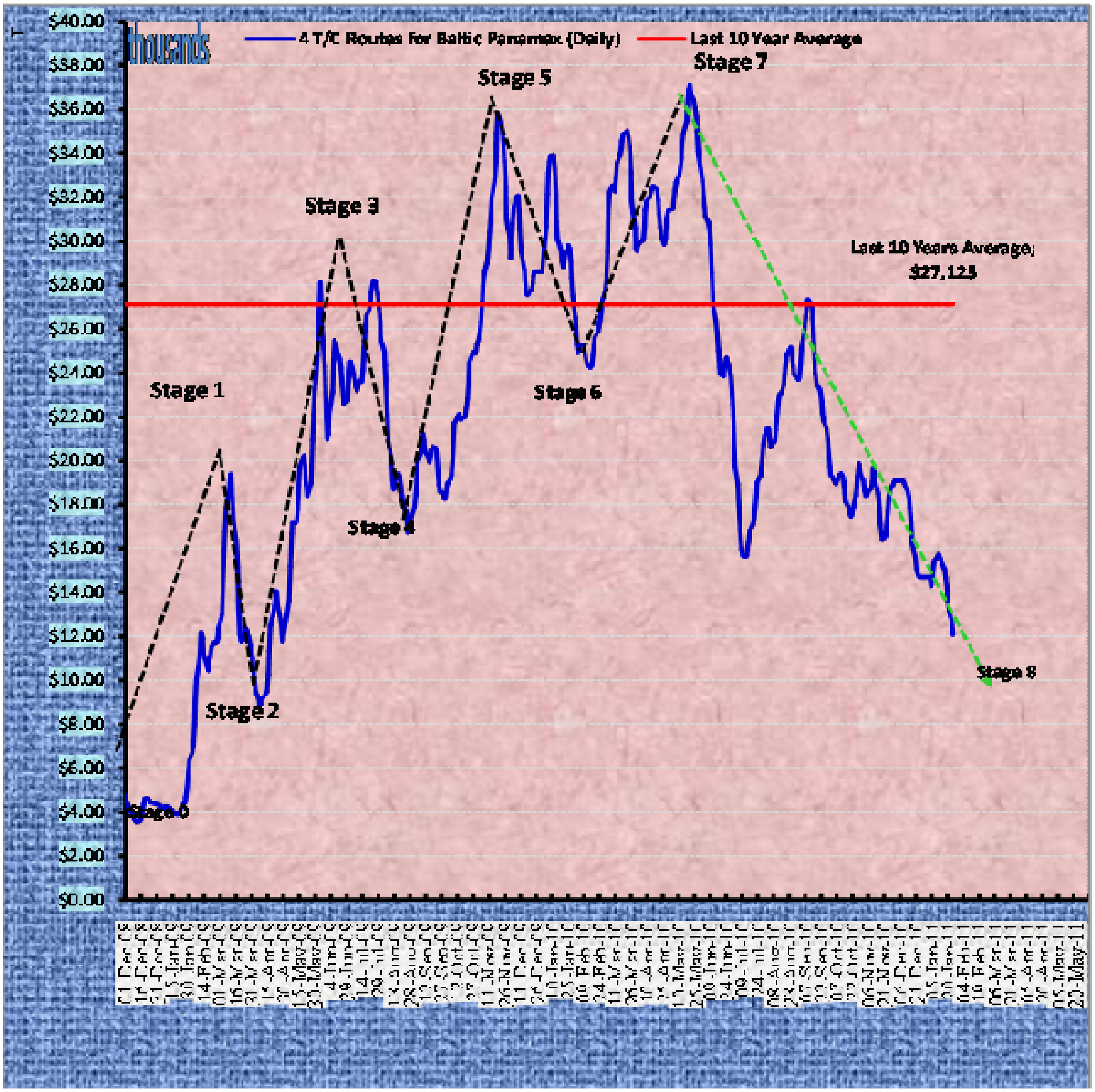

Figure 8. Hampton short cycle from 01/12/08 to end May 2011.
Source: Data from Clarkson's.

2 cycles from low to low; non periodicity is evident) freight rates 14 times lower than the one before ($50 000). Since end 2008, crisis resembles, or is even worse, than the 1981-87 one, with rates round $3 000. Survival will rest now, as then, on the existence of past profit reserves. Prudent companies build reserves by not distributing all profits to shareholders. Moreover, apart from survival, crises create opportunities for those with liquidity (second hand ships; asset playing).

Figure 8 is a chart –prepared by my student Dr Psifia- for the short Hampton cycle, showing forecasts up to end May 2011. The coincidence of actual freight rate line (blue solid line), with that of the idealized short term cycle (dotted black and green line) is very close. Stage 8 as an indication ended at $4 000 in May, 2011.

Forecasts are shown by the green dotted line (since 2010). Till May 2011, freight rates were below $11 000 and expected to fall to $5 000, the amount of stage 0. In fact, on 2nd February 2012, freight rate was close, i.e. at $5 409. The fall stopped at $5 409 (turning point up) on 2nd February, 2012. This value indicates also the end of the last short cycle, which started in end November, 2008 and lasted 38 months. According to Hampton's theory this period of short cycle is characterized by decisions that involve 'building and scrapping of ships'.

We turn now to the long-term cycles of MTA.

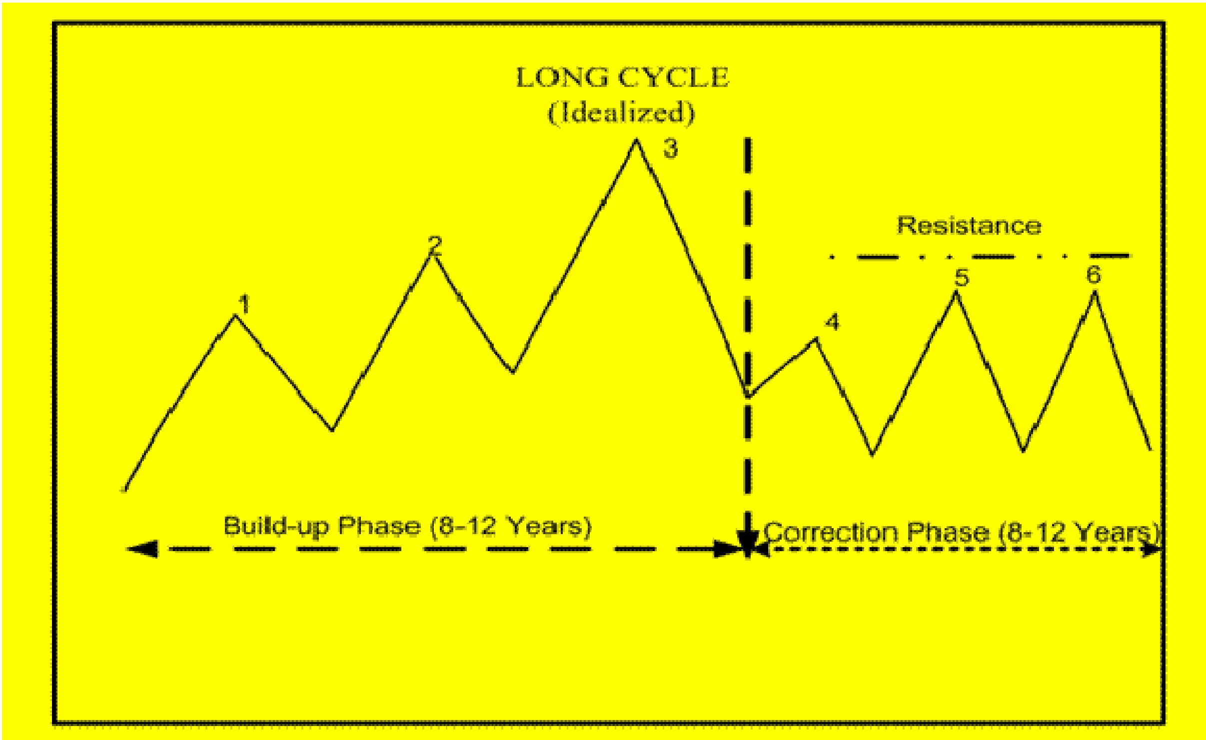

Figure 9. Idealized Long-run shipping cycle of 16-24 Years due to Hampton.
Source: Hampton (1990).

MTA lond-term cycles

In maritime technical analysis (1990), we encounter a long period of low freight rates, covering 8 to 12 years, the *correction phase*. Also, the build-up one with higher and step-wise rising freight rates. Both phases last from 16 to 24 years. Over-optimism during the build-up phase produces a surplus of ships, delivered by shipyards causing the end of it. As shown (Figure 9), the long cycle consists of 2 phases with 3+3 shorter cycles, 3 for each one, each covering 3-4 years. The 'build-up' phase consists of 3 regular cycles each rising higher than the previous one. The peak of $96 000 per day (1st Jan. 2008), caused an enormous increase in the capacity to own, build and finance. Ship ordering dominated this cycle and vast deliveries, as a consequence followed.

Figure 10 below, using actual numbers, shows the contemporary long shipping cycle of 16-24 years, as well as its correction and build-up phases. It started on 4th August 2003 at $16 000 freight rate; it rose in three steps to $47 000, to $51 000 and finally to $96 000. A fall then occurred on 5th December 2008, at a time charter of $ 4 058; it then rose to $36 000 and fell to $12 000 at the beginning of 2011. During this cycle decisions concern the question of remaining in the industry or leaving it, due to the longevity of the correction phase that a ship-owner must wait.

Freight rates are shown on the vertical axis, in $000, every 2 six-monthly periods per year from July 2011 to January 2018. Dates are marked on horizontal axis (Figure 10). The past (black line=actual freight rates), which followed the pattern of red dotted line, we believe, *guarantees* the future evolution shown by the green idealized future pattern/line. Consequently, in 2018, the Panamax time charter freight rate of 4 routes (BPI) will be below $22 000.

During build-up phase new investors enter the market and existing ones expand their fleet with new-buildings and by replacing older ships, with newer and larger ones (as this occurred also in the 1981-87 crisis). Owners are helped by shipyards and bankers to this end. Lastly, vast orders are placed because of the optimism created by the very high freight rates during these 8-12 years, and then deliveries take place, they create oversupply. Demand stays either steady or falling or falling behind Supply.

The *build-up* phase took place between 2003 and December 2008 (65 months or 5 years and 5 months; *shorter* than the theory of minimum 8 years). The *correction phase* started in December 2008; and is expected to end in 2016. The correction phase was *slow*. If we wait for scrapping process to bring equilibrium, this is twice as slow as other adjustments, and thus market needs time to arrive at equilibrium. Figure 10 indicates clearly forecasts into future up to 2018 using 'maritime chartists' methodology.

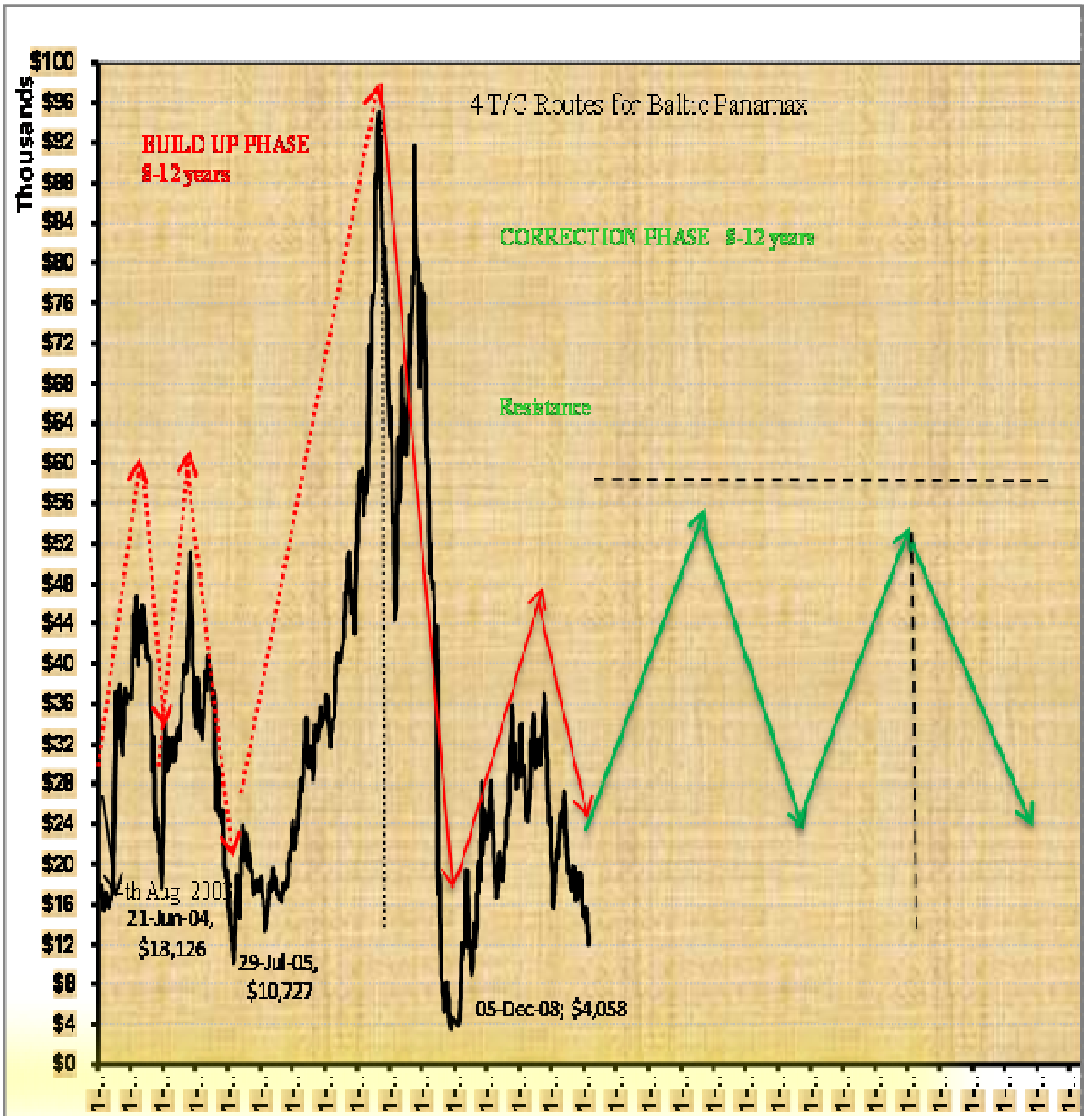

Figure 10. The 16-24 years cycle from 04/08/2003 to 2015.
Source: prepared by my student Dr Psifia. Data from Clarkson's.

CONCLUSIONS

Academia –maritime and general -tried to provide forecasting models for stochastic linear and nonlinear and chaotic time series with a short correlation and a long memory/dependence. Moreover, four schools emerged to manage risk and predict stock prices: Fundamental, Technical, Modern and Heretic. Reality, however, has confounded expectations based on models based on the assumption of 'efficient market hypothesis'. We saw in the economy in general, and in maritime economy, in particular, quiet periods interspersed with bursts of turbulence. When we allow nonlinearity into models, we saw that markets violate not only RW, but also martingale.

We run a series of tests for stationarity, normality, independence, long term memory and chaos in a diagnostic procedure. We kept at the back of our mind that is probable for shipping time series to have been generated by a nonlinear deterministic law of motion, like those found in the natural sciences. There, time series behave in ways that *look* random even when tested by the traditional statistical and econometric tests, but they are actually biased RW, *with long term dependence.*

Human desire to know future led people to resort, among other methods, to Technical Analysis. Even the mystery of the Arabic numbers and Fibonacci series, leading to the divine ratio, known since the time of Pythagoras, have been invoked to understand finance. Among Maritime economists, Hampton (1990) advanced a theory of two idealized shipping short cycles of 8 stages of 3-4 years combining to give a total cycle of 16-24 years. In practice, all these cycles were shorter or longer than predicted by at least ± 10%. This means albeit 3.6 to 4.8 months shorter or longer for the 3-4 years short cycle and 1.6 to 2.4 years for the long-term cycle.

Chaos theory provided predictions (of daily and weekly rates) of BPI for only 6 weeks ahead maximum. Using, however, 'chaos cycle theory' we detected cycles 28-35 months and 4 to 9 years. The benefit is also that Chaos theory supports the idea that cycles are non periodic – a serious mistake committed in the past with tragic repercussions for investors. Moreover, it was shown that cycles not only vary from ship size and from one period to the other, but also differ according to the duration of the research period. Fortunately, there is a general convergence to 3 cycle durations, as shown by chaos theory: around 3 years, around 4-6 years and around 8-12 years.

Last crisis cropped the height of the freight rates to below $40 000 per day. The long cycle started on 4th August, 2003, and is predicted to end in 2017-2018. Its correction phase will last 10 years (2009-2018), whereas its build-up phase before it took 5.5 years. Phases, too, like cycles are uneven.

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Appendix 1: Test for the existence of chaotic dynamics.

Even if a time series looks random (Figures 4 and 8), it might still be deterministic (Siriopoulos, 1998). The new element since 1985, and especially since 1987-89, however, is that chaotic signals must be analyzed in the time domain called ‘state space’ of the system (or ‘phase space’ (A graph that allows all possible states of a system)). Moreover, simple nonlinear models, though free of autocorrelation, can exhibit strong nonlinear dependence (Granger and Andersen, 1978). Mandelbrot (1963) argued that in uncorrelated returns large variations tend to be followed by large variations. This led Engle (1982) and Bollerslev (1986) to invent ARCH and GARCH (GARCH stands for the Generalized, (meaning that it has been broadened to accommodate more circumstances than ARCH in 1982), Autoregressive (AR), Conditional (meaning that the changes in the variability are controlled by data’s own past behavior), heteroskedasticity (meaning that data’s variability changes with time)) models respectively (dealing with a time varying variance), but there are still certain anomalies in these models.

Depending on the dimension of chaos, this system can be predicted, if we know: (a) the sensitivity on starting conditions and (b) the dimension of the system; a system is predictable if it has fewer than 10 dimensions. For the identification of a chaotic time series, we have to construct first a pseudo-phase space using all possible states of the system using the ‘time delay method’ (Packard et al, 1980).

System’s dimension (To analyze the problem of chaos in financial time series there are two methods: (1) the dimension approach, used here, and (2) the approach with artificial neural networks)

Using the correlation dimension, we can find system’s dimension [Grasberger and Procaccia (1983)]. There is a number of dimensions where the correlation dimension stabilizes at an increasing embedding (The idea is to embed time series in successive dimensions until we see (if dimensions are ≤4) a clear picture of the object (i.e. the attractor) that is formed. This is done using as few equations as possible) dimension. This dimension applies also to the relevant attractor (This is an object expressing the equilibrium level of the system) of the system. Here, as shown in Figure A, the correlation dimension – cd is equal to a stable number 1.27, which is less than 2, i.e. is fractal, at an embedding dimension 18, calculated by the computer program NLTSA (2000). White noise does not permit stabilization. This 1.27 also satisfies the Eckman and Ruelle rule (Eckman J-P and Ruelle D, (1992), ‘Fundamental limitations for estimating dimensions and Lyapunov exponents in dynamical systems’, Physica D 56, pp. 185-187) (1992) that cd≤2log2815=6.9. Time delay (The system of time delay τ is a method to create another variable for each dimension, where we have only one variable) is set equal to 1 [Siriopoulos and Leontitsis (2000)]. So, the BPI 1999-2011 per day time charter rate is chaotic of a dimension ≅ 2 which is less than 10 (so, we have a low dimensional and predictable chaos).

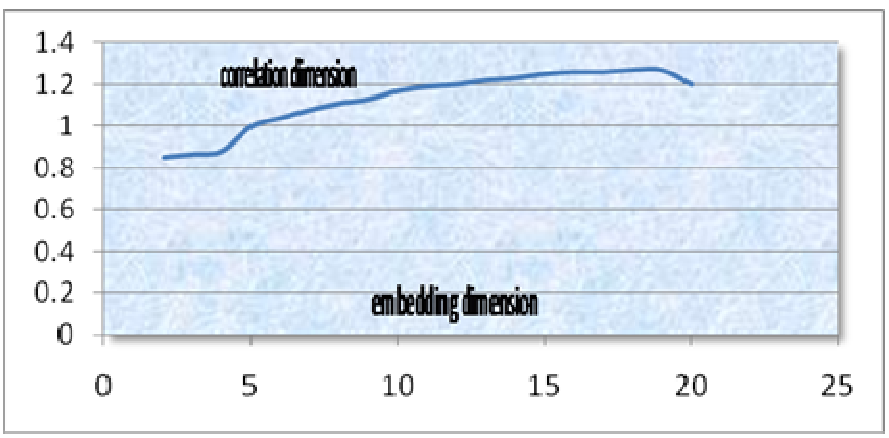

Figure A. System dimension by Correlation dimension versus embedding dimension.
Source: Excel and NLTSA V.2.0 (2000).

Lyapunov's exponent (A measure of the dynamics of an attractor. If positive, it measures the sensitive dependence on initial conditions): To find this we will use the method developed by Kantz (1994), which is robust and not influenced by the embedding dimension chosen. The attractor has a dimension of 1.27, as mentioned. NLTSA gives us the values of time evolution S(*a*) and evolution *a* for the first 5 values of *a*, including 0. The maximum Lyapunov exponent λ_1 is given by the slope of the curve in Figure B, which is determined by: S(*a*)=$\lambda_1 a + c$, where c is a constant.

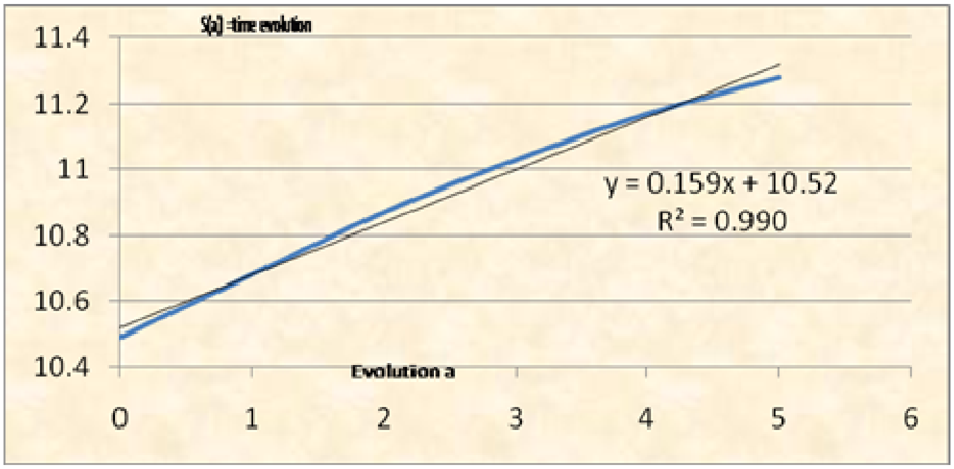

Figure B. Lyapunov exponent by the slope of S (*a*) = $\lambda_1$1+c.
Source: Excel and NLTSA.

As shown (Figure B), the Lyapunov exponent is equal to the slope of the curve, i.e. 0.1594, where the probability of error (1- R^2) (Where R^2 must be ≥98%) is equal to 0.0098, which is small in the area where *a* is in the closed interval [0-5]. The exponent λ_1 is positive as it should be, and allows us to forecast 1/0.1594 days ahead i.e. 6.27 or 6 days. This is a very short period.