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The Multi-faceted Character of Risk in Maritime Freight Markets (Panamax) 1996-2012.

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Abstract

The paper deals with *maritime risk*, which we consider important, no doubt, for ship-owners acting in volatile markets. Traditionally, risk is measured by 'standard deviation'. Other risk measures like 'excess kurtosis', 'excess skewness', 'long-term dependence' and the 'catastrophe propensity' were ignored. Risk in 1900 was based on the mathematical laws of Chance and influenced greatly by Probability theory due to Pascal and Fermat (1654). Economists, but maritime ones, have understood, however, that the 'random walk' model, and the 'efficient market hypothesis', failed to interpret reality since Black Monday (1987) at least. The traditional treatment of risk assumes that 95% of the observations fall within 2σ from their mean. However, the daily data of 4 time-charter routes ('Baltic Panamax Index', May 1996-February 2012) showed otherwise. Moreover, variance varies from one decade to next, even under stable mean. Risk is related to *dispersion*, which is defined the same in 'normal' and 'chaotic dynamic systems. All maritime studies (1997-2013), however, reported excess skewness, excess kurtosis, absence of normality and serial correlation...but no remedy provided. As far as the reference to the assumption that observations are 'independent and identically distributed' is concerned, maritime time series analysis shows 'long term dependence' indicated by a high 'Hurst exponent'~1. The paper uses 'Rescaled Range Analysis'-a nonparametric method, to identify the 'Noah effect' (i.e. the propensity of time series towards catastrophe; measured by alpha exponent). Combined with nonlinear forecasting methods, short and long term risk is thus in this paper forecast. Finally, it shows using daily data, that 'risk and dependence' vary on data's calendar time used.

JEL Classification: C65, C53, E44, G17.
Key-words: Risk, excess kurtosis-skewness risk, non-normality risk, long term dependence, 'Noah' effect, forecasting catastrophe's risk, BPI 1996-2012, Hurst exponent.

1. Introduction

Statistics science inherited us the 'square root of variance', or 'standard deviation', as the *measure of risk,* derived from normal distribution. But, 'how many distributions are normal, and have a well-defined standard deviation'? All maritime time series published during last 20 years exhibited *excess skewness and excess kurtosis* (Table 1), which is a serious *departure* from normality; this invalidates, or drastically weakens, not only the *validity* of the results derived, but also the *level of actual risk*. Moreover, the basic assumption of normal distribution that 'observations are independent' is questioned.

The paper presents a number of non-maritime and maritime time series (for freight indices), which have *deviated* from normal distribution. In such cases, the *additional risk, over and above* that indicated by standard deviation, has to be faced. It is high time for maritime economists, we reckon, to evaluate the *impact* of *all* risks, which are created in the freight markets. This is also the idea of this paper. Normality departs also with long-run correlation. The paper also predicts the risk towards catastrophe or 'Noah Effect'[1], which occurred on 12th December, 2012 (an unexpected shipping depression begun).

The paper is organized as follows: next is literature review of shipping and non-shipping papers. Then the definition of risk in terms of standard deviation is presented. This is followed by an account of risk as it is met in chaos theory. Risk is also shown in the context of 'modern finance theory'. Then, empirical evidence is presented for the risk encountered in one of the main freight rate markets i.e. the Panamax. Empirical evidence is used to illustrate how risk is treated, when observations are *dependent*. The outcome of this discussion leads to short- and long-term forecasts of catastrophe risk. Moreover, 'calendar risk' –first defined by us- is also revealed. The paper finishes with conclusions.

2. Literature review

Osborne (1964) plotted the density function of 'stock market returns' and found it 'approximately' normal; the distribution was «κυρτή»/it showed a kurtosis. Tails were fatter than normal. Cootner (1964) admitted that tails are fatter in price changes, but the '*sums of normal distributions'*, he argued, are Gaussian. Investors are *rational* and returns are '*approximately' normal and independent*. He ignored, however, the real possibility of a *nonlinear* reaction to information.

Mandelbrot (1964) argued that returns belong to a 'stable Paretian distribution', where variance is *undefined*. Fama (1965b) found daily returns *negatively skewed* with fatter tails and higher peaks (meaning leptokurtosis). Sharpe (1970) argued that for annual returns, a normal distribution assigns *low probability* to the occurrence of really *extreme* values, *at odds with real events*. Kraus and Litzenberger (1976) tested for skewness in a CAP model, using NYSE stock prices (1926-1935). They found a significant risk-premium. Fang and Lai (1997) derived, too, a CAPM with mean, variance, *skewness and kurtosis*, and estimated the influence on returns of NYSE stocks (1969-1988).

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[1] The 'Noah effect' occurs when a price (or freight rate) changes either up or down, and this is considered by 'some' that may ride and by others as a catastrophe'.

De Vries (2001) in studying the relationship between 'pound and guilder' (1609-2000!), and the behavior of speculative prices, paid special attention to the *extreme* movements caused by *fat tails*. During periods of turbulence, asset prices *gyrate* and *produce extreme values*. They also come in *clusters*[2]*;* i.e. a clustering of volatile episodes and periods of quietness, with self-scaling[3] volatility. The empirical density was *too peaked* and the *tails were too fat*.

Modern finance helped us to understand the importance of its assumptions *under the face of real events* (e.g. 'dot-com crash', 2001; Black Monday 1987) (Johansson, 2005). If the *mean and variance are only used, they give unsatisfactory description of market equilibrium*. Important factors are left out, which remain un-priced[4]. He used 600 different stocks (1979-2004), and examined the existence of positive risk premiums for 'skewness and kurtosis' in 'Swedish stock market'. The distribution of stock returns found *seldom normal*. The effect of kurtosis on asset pricing gave a risk premium of ~ 0.8% p.a. *Skewness, however, had a risk premium of 7.45% p.a. Thus the* performance of CAPM can be improved by incorporating the 3^{rd} and 4^{th} moments[5]. Moreover, the explanatory power, given by R^2, is 32% when mean and variance are used, but *rises to 70% when skewness is added…*

Maymin (2011) recognized the problem of *fat tails* and the *more frequent crashes* in security prices, and proposed a model more closely matching real world compared with that of 'random walk'. His model *allows* for *higher* kurtosis and a more *negative* skewness.

Kavussanos (1997) argued that volatility is high during and immediately after periods of large imbalances and shocks. Goulielmos and Psifia (2011) showed, econometrically, that the effect of the October 2008 banking crisis on freight rates, two months later, *caused a 9.6σ departure from mean*, while the 1973 oil crisis caused a departure of *only 7.04 σ*. Black Monday for stocks in 1987 was, however, more violent, producing a 22σ departure of Dow.

Grammenos and Arkoulis (2002) examined the relationship of certain 'global macroeconomic sources of risk'[6] with 'shipping stock returns'[7].The higher 'oil prices' and the 'greater number of laid-up ships' affected returns *negatively*. Improved foreign exchange parities of currencies to \$, also affected returns *positively*[8]. Authors reported *negative skewness and positive excess kurtosis* in all their cases. The long term world market 'beta' found to be 0.81<1 (rounded).

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[2] The stability of economy in the distant past, was secured by 'gold standard' (1875-1914), and the restoration periods following the 2 world wars. Increased volatility caused by 4 historical events of turmoil: the Napoleonic Wars, the 2 World Wars, the 1929-33 depression and the post 'Bretton-Woods' period. He mostly confirmed the work of Mandelbrot (1963).

[3] Engle (1982) recognized the problem of scaling volatility and proposed ARCH as a remedy (the autoregressive conditional heteroscedasticity model).

[4] Unlike skewness, kurtosis did not receive equal attention in research.

[5] Fama and French in 1992, found that 2 effects, namely the 'Price/earnings' ratio and the 'market/book' ratio, identified the profitability of a stock, making 'beta' redundant.

[6] Industrial production; inflation; oil prices; exchange rates and laid up ships.

[7] 36 listed shipping companies; 10 international stock exchanges; 6 Countries.

[8] Grammenos and Marcoulis (1996) examined a cross section of shipping stock returns with the aid of microeconomic factors; also see Kavussanos and Marcoulis (2000).

Kavussanos and Alizadeh (2002) found that 'price series' and 'operating profits' were polykurtic; normality test indicated significant departure. Data exhibited serial correlation. Alizadeh and Nomikos (2003), in an EGARCH-X[9] model, connected 'price volatility' and 'trading volumes' (1991- 2002) for 2nd hand dry bulk ships and found *negative skewness* in all series, but Panamax, even at 10% significance level. All series showed *excess kurtosis*. The 'Jarque-Bera test' showed significant departure from normality. There was also present serial correlation.

Mulligan and Lombardo (2004) examined 12 maritime equity price series for 'behavioral stability' and 'efficient market pricing' (1989-2002). They concluded that there was evidence *against* efficient valuation, that 'asset returns' follow a multi-fractal model, that the '*efficient market hypothesis*', in its weak form, should be rejected, and that certain equities exhibit anti-persistence, meaning persistent overreaction to new information, or 'pink noise'[10].

Jing et al (2008) investigated the impact of external shocks on 'volatility' in daily 'returns' on dry bulk freight rates, distinguishing between 3 sizes of ships (1999-2005), using GARCH and EGARCH. Dry bulk cargo is characterized by *high risk and volatility.* All series were *skewed with fat tails and spiked peaks*. Moreover, they found high autocorrelation.

Drobetz et al (2010) examined certain macroeconomic risks[11] in the monthly shipping stock returns for containers, tankers and dry bulk carriers (48 listed companies, 1999-2007)[12]. Their model, based on the 'seemingly unrelated regression', showed that shipping stocks exhibit remarkably *low stock market 'betas*'. Their model assumes that the *market correctly prices each shipping stock* (Fama, 1965a) and prices/freight rates vary smoothly and independently from one instant to next. We may remind that conventional methods *consistently* underestimate[13] betas.

El-Masry et al (2010) investigated the impact of[14] 3 factors on stock returns (1997-2005), using a multi-factor OLS. They found a low incidence of the first two. Oil prices had a significant *positive* effect on a minority of shipping firms. Shipping stock returns were negatively influenced by oil prices, while returns benefited from a depreciated \$. Capital costs were not affected, though covering 50% of total cost of newly built ships (Kendall and Buckley, 1994; Stopford, 2009).

Chen et al (2010) investigated 'daily returns' and 'volatilities' (Cape, Panamax) on 4 major trading routes (1999-2008). They found constantly changing. Their results were mixed; they found substantial *excess kurtosis*. As a result they used 'the Bollerslev

[9] GARCH= generalized auto-regressive conditional heteroscedasticity. It is a 'generalized form' of ARCH, to accommodate more cases. It is 'autoregressive' conditional as changes in variability are controlled by data's past history. The innovative element is that data variability is changing with time (=heteroscedastic). EGARCH, due to Nelson (1991), moreover uses *exponential variance*.

[10] Pink-noise=anti-persistence according to Rescaled Range Analysis; time series is reversing more often than random.

[11] Change in the trade-weighted value of US\$; change in G-7 industrial production and change in oil price.

[12] In 2008, returns for tankers fell 44% and of bulkers 69%.

[13] From research carried out in France (2000).

[14] Exchange rates, interest rates and oil prices on stock returns of 143 shipping companies in 16 countries.

and Wooldridge 1992 model', which uses quasi-maximum likelihood. *The Jarque-Bera test rejected normality in all cases*.

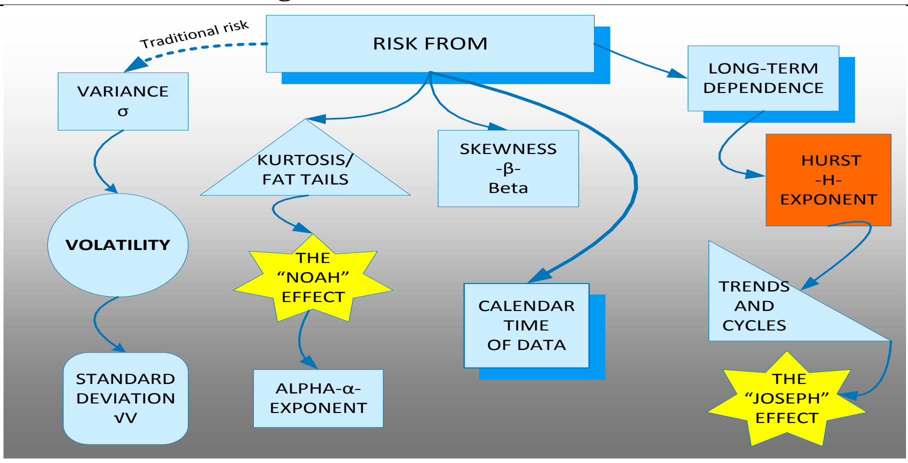
Pruyn et al (2011) reviewed about 20 papers on 2nd hand vessel value estimations (1992- 2006). Kavussanos and Alizadeh (2002) and Adland and Koekebbaker (2004) assumed that the different ship size segments are (sufficiently) *independent.* Sodal et al (2006) argued that both tanker and bulk markets are *integrated,* a la Beenstock. Stopford (2009) argued that tankers and dry cargoes ceased to move together (1975-1995). Surely here there is much contradiction. Sufficient *dependence* or *lack of integration* means…*correlation*. Consecutive price changes should be independent. This condition is unlikely to be met; if the observations are correlated, or exhibit serial correlation, the *usefulness of standard deviation used as a measure of risk is considerably weakened* (Peters, 1996).

Summarizing, most studies measure the impact of *excess skewness and excess kurtosis* on returns. But, maritime studies were satisfied only to report *excess skewness, excess kurtosis, non-normality and correlation*, while the impact of these features on results was completely left aside.

3. Risk as expressed by the standard deviation

An overall picture of Maritime Risk is presented in Figure 1. As shown, risk comes from five sources.

Figure 1: Risk and its sources.



Standard deviation – indicated by Greek letter σ –measures traditionally risk. This is the 'statistical concept of *dispersion* of observations from their mean' (Figure 2).

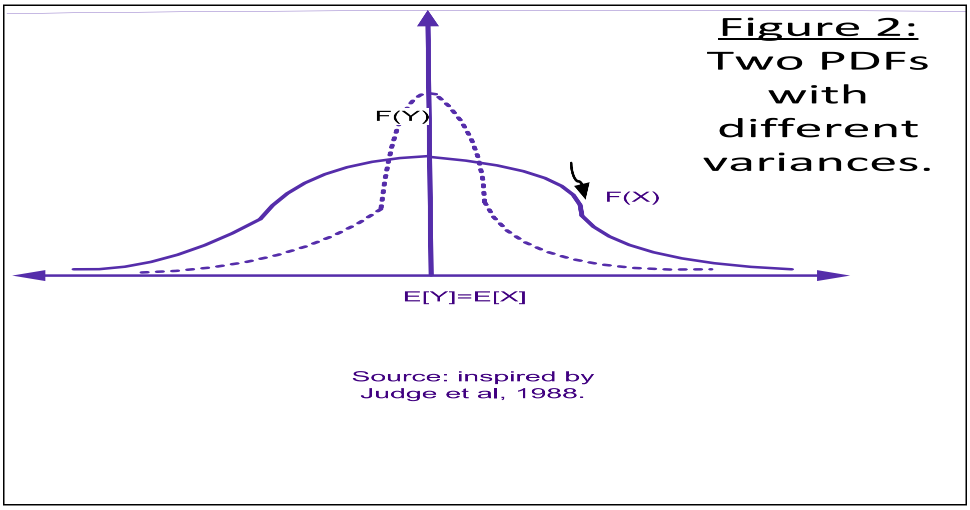


Figure 2: Two PDFs with different variances.

Figure 2 shows that a *random variable X* -and another random variable Y- sampled over an infinite number of times, with the same mean, has variance (risk associated with X) greater than that of Y (risk associated with Y). In statistical[15] terminology this means that the probability mass of X is more *spread-out,* showing a *wider dispersion* of values of X from the mean (Judge et al, 1988). Standard deviation is the mathematical yardstick for measuring 'scattering of data'; σ is a measure of risk, *on the assumption that the distribution is normal*. If returns come as *expected*, within the frequencies of 1σ, 2σ and 3σ from the mean, then 'normal' risk = 'real' risk, with small and unimportant rare exceptions.

Risk, however, is a river collecting waters from many sources (as shown in Figure1): from kurtosis[16], if kurtosis coefficient > 3[17] (the so called kurtosis risk)[18]. Two distributions *with same mean and variance* can have a different kurtosis (Figure 2). The existence of *fat tails* implies *many large extreme outcomes*. This is a serious risk that may create unpleasant surprises (Turner and Weigel, 1992). In addition, Risk is due to *long term dependence* of price/freight rate changes; and to *skewness,* as well as due to calendar time used.

Risk caused by skewness[19] appears only when observations *are not spread symmetrically* round the mean. *Ignoring skewness* –as maritime economists do- leads to *under-estimation of risk that could be brought-in by* skewed variables. Moreover, skewness affects *hypothesis testing*, because *such testing is not possible*. The probability of extreme values -estimated by normal distribution- is only 2%, and maximum dispersion can only be 3σ from the mean. However, reality shows differently (Goulielmos and Psifia, 2007). The statistical characteristics of the 'Dow frequency distribution of returns' (1888-1991) of 5 and 90 days, exhibited changes of

[15] Correct, if the effect from peak = the effect from fat tails http://www.riskglossary.com/articles/kurtosis.htm

[16] Kurtosis: $K=E\{(Rt-\mu)^n\}/\sigma^n$, where n=4 and Rt = return of an asset at time t, μ= mean and σ= standard deviation.

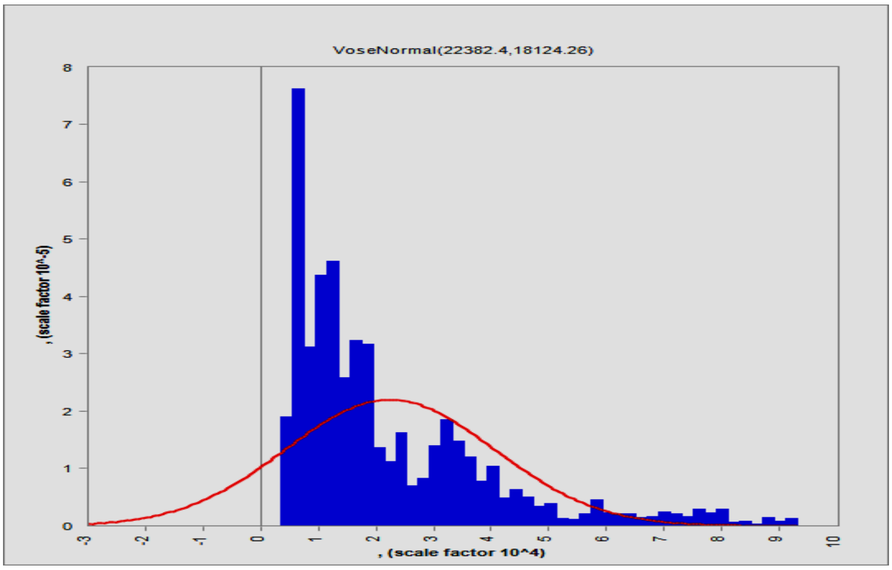
[17] The yardstick = 3 (normal distribution).

[18] *Excess* kurtosis: $EK=M_4/M^n{}_2-3$, where n=2 and M is the corresponding moment shown by its subscript. Normal distribution EK=0. If EK≤0 we have a *platykurtic* distribution=fat in the center, thin in tails. The leptokurtic requires EK≥0 = thin in center and fatter in tails.

[19] Skewness: $S=E\{Rt-\mu)^n\}/\sigma^n$, where n=3. ES=excess skewness = $ES=M_3/(\text{square root of } M_2)^n$, where n=3. ES=0 for symmetry. ES>0 = positive skew. ES<0 =negative skew.

4σ (Peters, 1994). For 4σ, the real probability is 1%, compared with normal 0.01%. Daily traders faced risk 6σ. Same situation is with 'bonds' or 'foreign currencies'. Fat-tailed distributions imply *long term determinism* for 'stocks and bonds'. 'Dow's log returns distribution raw data' (1928-2008) exhibited also 'skewness and high kurtosis'[20]. Investigating volatility of the 'S&P 500 daily index' returns (1928-1989), on 2 occasions, the market shifted by large amounts: in 1940s and in 1970s, due to 'skewness and kurtosis' (Turner and Weigel, 1992). If one estimates risk in stocks by standard deviation, this *is almost the same,* in these two *markedly different* periods: one during war and one during energy crisis. On **Black Monday**[21] kurtosis was 80, while in the '1920s depression' was 19. So, same risk *varies between periods*. Even with a low standard deviation, as in 1960s, there were *serious 'skewness and high kurtosis'*. The mean was almost stable over these 60 years. In addition, the 'S&P 500' exhibited 4σ and 5σ departures from their mean in both tails. If stock returns are not normally distributed, the *statistical analysis, and especially the diagnostic tests of correlation, t-statistics, random walk*, *are seriously weakened and misleading* (Peters, 1996; Goulielmos, 2010a). The existence of skewness and kurtosis in maritime markets is shown in Figure 3.

Figure 3: Actual and normal distribution fitted on the "average over 4 'time charter' routes for Baltic Panamax Index", $ per day, (06/05/1998-16/02/2012) (n=3450).



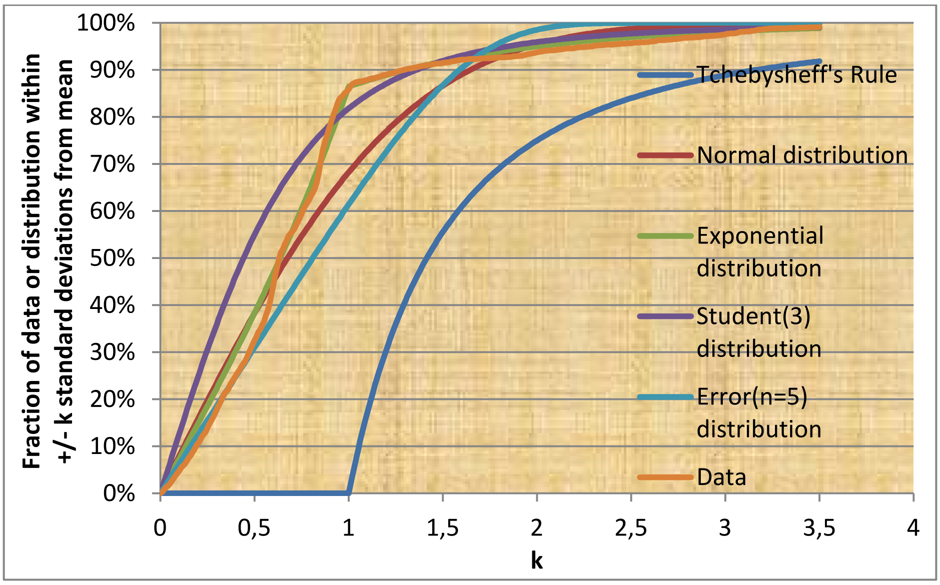
Source: Clarkson's Data; Vose software. Normal distribution is indicated in red.

BPI time series exhibits *excess kurtosis* of 2.43 (5.43-3) and *excess skewness* 1.62. The high peak indicates the risk coming from kurtosis, while skewness is shown at the

[20] http://www.skew-lognormal-cascade-distribution.org/apps/dji_main.php where *short memory* models (=ARCH; GARCH) are inappropriate.
[21] Another day became famous: the 'Black Tuesday'. This is the 29th October, 1929, where stocks lost 13% and signaled the start of great depression. The market lost $14b (downloaded 30/10/2013 from "InvestorWords.com").

right tail, which extends *above* and *beyond* normal. Jarque-Bera test = 1,324.8>5.99[22] rejects moreover normality. Lihn (2009) argued that "statistics under fat tailed structures deviate significantly from that of normal distribution".

Figure 4: Comparative presentation of 6 curves based on 5 different distributions including Normal and BPI (data).



Source: data and 'Vose software'.

As shown in Figure 4, the BPI data goes beyond the normal limit of 3σ. The 'Tchebysheffs Rule'-TR applied here, which is applicable to any probability distribution or data set, states that for any number k>1 at least ($1-1/k^n$) (where n=2) of the measurements fall within k standard deviations from mean. BPI observations up to 2σ are 75% (TR= dark blue) and not 95% (as argued by Normal); even for 99.89% probability and 3σ, the rule gives 90% of observations. Therefore a 10% of values of BPI are went out of the 3σ and naturally are those that may create great surprises…

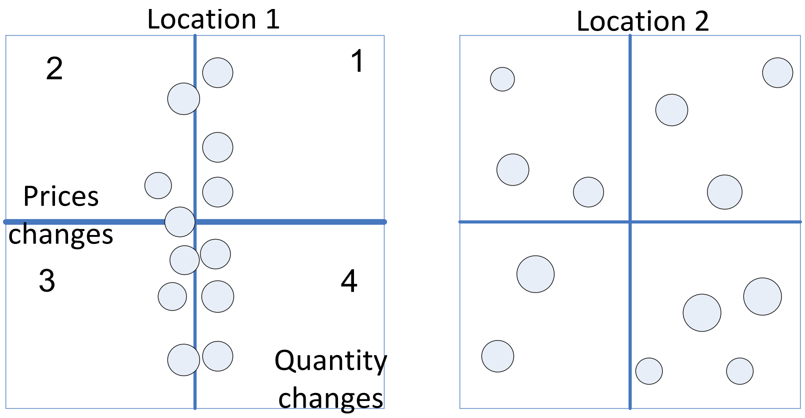
4. Risk in chaos theory

Dispersion is also a sensible measure of risk in a nonlinear dynamic framework[23]. Risk, but also opportunity, is indeed found only in *high-order chaos*. Consider two scatter figures of *changes* in quantities and in prices sold in 2 different 'retail' locations of a single good (oil; Figure 5).

[22] JB = N [($skew^n/6 + (kurtosis-3)^n/24$)], where n=2.

[23] Chaos is a deterministic nonlinear dynamic system producing *random-looking* results. High order chaos has more than 10 dimensions, determined by more than 10 equations. Chaos assumes a fractal dimension and sensitivity on initial conditions.

Figure 5: Scatter diagrams of price and quantity changes in two retail locations of a single good sold (oil).



Source: Inspired by Priesmeyer (1992).

Each scatter picture above is a '*phase space*'[24]. The points, if joined together by preserving their chronological order for the last 2 years, form an *attractor*[25]. The attractor is a 'limit cycle'[26] (Figure 3). The left picture is bound to price changes. The right shows dispersion of points, reflecting *larger changes* in both prices and quantities. The sale pattern in left is *tightly constrained to an identifiable attractor*[27]; in right market characteristics allow *much greater variability*[28]. The two parts differ by the *period* of their 'limit cycle'. The right has a period of 8, indicating high-order chaos, a situation that is frequent in management. The repeatable pattern is unclear here and the limit cycle retraces its trajectory every two years. It is too complex to predict. It results from a *turbulent*[29] internal environment. D*ispersion* in dynamic systems is synonymous of risk. In a dynamic framework, *volatility and risk* are *comparable* to '*standard deviation*' (Peters, 1994).

5. Risk as conceived by modern finance

Investors and academia rely heavily on 'modern finance'-MF, which emerged when mathematicians studied…Chance; it assumes that 'prices are not predictable'; their fluctuations can be 'understood only by the mathematical laws of Chance'. Moreover, '*risk is measurable and manageable*'.

MF goes back to 1900, to the work of mathematician Bachelier on financial markets[30]. He rested on the work of mathematicians Pascal[31] and Fermat[32], who have

[24] It allows all possible states of a system (past, present, future).
[25] The attractor, in nonlinear dynamic series, defines the *equilibrium* of the system.
[26] This is an attractor, for nonlinear dynamical systems, that has periodic cycles (orbits) in its phase space. The points in the scatter figures are *attracted* to a cycle.
[27] Creating an equilibrium point and stability, is a pattern of consistency and constraint, where powerful and restrictive forces are in action.
[28] Volatile market; sensitive to adjustments.
[29] Management decisions are characterized by ignorance of the structural patterns of change that shape one's organization, a situation difficult to manage…
[30] In the English-speaking world it goes back to 1964, when Bachelier's doctoral thesis was translated into English.
[31] Blaise, 1623-1662, French mathematician, physicist and religious philosopher.
[32] Pier De, 1601-1665.

invented 'probability theory'. He applied probability theory to deal with 'French government bonds', using 'random walk'. *Prices rise or fall with equal probability*. This is also a *fair* game, with neither profit, nor loss in the long run. Bachelier wanted to estimate how much prices would vary mathematically. Random walk became later the 'Efficient Market Hypothesis'[33]; then in an ideal market all relevant information is priced (reflected in security price). *Yesterday's change in prices does not influence today's prices, or today's change in prices does not influence tomorrow's prices. Each price change is independent from last* - fulfilling one condition of normal distribution.

In financial economics *only variance expresses risk*; moreover, 'beta'[34] was established, on the common belief, that 'if one wants to gain more, he (she) has to risk more'. Investment portfolios are also classified by their probability of risk. A fund manager can build an *efficient portfolio* by pursuing: a specific return *and a desired level of risk*. Earning more and risking less, means to change the mix of volatile and stable stocks, or the mix of stocks, bonds and cash.

How MF can explain why the founders of a fund[35] collected \$7b, and at the end failed (during the 1998 Russian crisis). Several banks reluctantly agreed later to bail it out by paying \$3.6 billion for a takeover (Krugman[36], 1998; Hudson and Mandelbrot, 2004; Scholes, 2000[37]; Jacque, 2010). Krugman (1998) argued that above principals suffered from *myopia*. They overlooked *kurtosis, caused by the* debacle in Russia, the stalemate in Japan, and the market crash in USA. Apart from kurtosis, the 'long term dependence' was also ignored.

Economists measure market risk by *volatility, quantified by standard deviation, as mentioned*. The question is why stocks show much larger fluctuations? Many stocks lost 1/3 of their value in 2002. Also, in 2011, 'NIKKEI 225' lost 18%, 'DAX' 15.4%, 'FTSE 100' 7.5% and 'Athens Stock Exchange' 54%. According to standard model of finance, if prices change in accordance with normal distribution, the probability of ruin (i.e. if wealth falling below a desired threshold) *is approximately* 10^n (where n = -20). But reality has taught us to expect such events with higher probability. Fama investigated 30 blue chip stocks in Dow, and found that the big price changes were 2000 times *more common*. This means that a *major event* comes once in 3 to 4 years.

'Amaranth Advisors LLC' (2000) in 'natural gas derivatives' used 'Value at risk'-VAR, based on normal distribution, and found a VAR of \$1.33b with 99.9% probability; later this really rose to \$3.29b and even higher…(Jacque, 2010).

The tools for measuring risk provide results that underestimate it as they *presuppose* a non existing 'random and mild' world. The world is full of frequent 'Joseph' effects

[33] EMH = a 'broader variant of Bachelier's thinking'. Also, the 'intellectual bedrock on which orthodox financial theory sits'.
[34] This is the amount (or %) by which a stock price reacts to market. If a price stock falls 4%, and market falls 2%, = two times more volatile.
[35] Scholes and Merton -Nobel laureates for CAPM (1993)- 'Long-term Capital Management LP'.
[36] http://www.slate.com/id/1908 'Rashomon in Connecticut' 02/10/1998 retrieved 24/01/2012.
[37] Scholes (2000) announced an appeal for supervisory bodies (BIS) to support studies on stress-tests and concentration methodologies; "Planning for crises is more important than VAR (value at risk) analysis".

(cycles/trends) and more rarely 'Noah' effects (bubbles/depressions/recessions). Maritime economists are well aware of the 1981-1987 depression and the end-2008 one. It is in shipping that great fortunes are made and lost, and millionaires are created and disappear. Shipping deserves better modeling of the risks involved.

6. Risk in freight rate markets

Goulielmos (2009) dealt with risk using 'Aframax' tankers freight rates (1976-2008). He found that risk, demonstrated by 'long term volatility', is higher than normal. Volatility did not have the theoretical speed of the square root of time (Einstein, 1905) assumed for 'random walk'. Alpha found 1.56, indicating a very strong variation. Moreover, alpha, <2, points to a model specification of 'Pareto or Fractal' type distribution. Goulielmos and Psifia (2009) found alpha 1.38 in the 1 year time charter *weekly* rates for a 65,000 dwt bulk carrier (1989-2008), indicating greater volatility than that found in 'Aframax' ships (using *monthly* figures; mentioned above).

Table 1 summarizes the results of 8 previous shipping studies concerning skewness, kurtosis, absence of normality and correlation. Important is that when normality is rejected, *one has to think more carefully about the type of model that is appropriate for data. The model rejected should be changed* (Steawart and Gill, 1998).

Table 1: Evidence of Skewness, Kurtosis, Correlation and Non-normality in Shipping Papers (2002-2009).

Paper by	Skewness	Kurtosis	Normality	Remarks
1. Grammenos & Arkoulis (2002), 'shipping stock returns' (1989-1998).	Negative	Excess		Betas=0.81 & 0.79
2. Kavussanos & Alizadeh (2002), '2nd hand & new building prices' (1976-1997).			Significant departure	Polycurtic; serial correlation.
3. Alizadeh-Nomikos (2003) 'ship prices' (1991-2002).	Negative, at 10% s.l., except Panamax.	Excess: (round.)= 3.2, 8, 2.2 Handys, Capes & Bulks.	Significant departure	Serial correlation
4. Adland & Koekebakker (2004), '2nd hand market' (1976-2003).	Negative in VLCC & Aframax; positive Cape and Panamax; -1.54	Heavy positive (1976-2001) 0.04 for 5 years old 85k tanker	Definite rejection	

5. Mulligan & Lombardo (2004), 'maritime equities' (1989-2002).	Inefficient valuation	Pink noise		A multi-fractal model is suitable
6. Syriopoulos & Roumpis (2006), 'trading volume-prices' and 'return volatility' in dry and tanker's 2nd hand markets.	Negative at 10% s.l.	Yes	Departure from	
7. (A) Jing-Marlow-Hui, 2008, (1999-2005).	Positive: (round.) 0.03, 0.24, 1.8 BCI, BPI, JEHSI.	Excess (round.): 5.3, 7, 34 =fat tails, spiked peak	Rejected	Great autocorrelat-ion.
8. (B) as above (a) 1999-2002 (b) 2003-2005.	Positive 0.85, 0.18, 0.19 (1999-2002), -0.16, 0.22 and 1.49	(round.) 7.9, 5.1, 7.1 and 3.6, 4.7, 21, fat tails, spiked peak	Rejected	Skewness - kurtosis did not increase after splitting period
9. Goulielmos 2009, BPI weekly, (1998-2008).	Negative 1.94.	21.81	Rejected	Chaotic model

As shown (Table 1), 8 papers report skewness, kurtosis and absence of normality. The above papers did not investigate the impact of skewness and kurtosis on risk calculations. They rested on GARCH model. This admits that a distribution can *vibrate*, and when volatility jumps, new parameters cause normal distribution to *grow*, and vice versa. But no answer is given as to what are the deeper underlying causes of vibration.

GARCH has marginally persistent values, insignificant at 5% s.l. It is not self-similar; its parameters appear to be period-dependent and not constant in a scale adjustment. Certain time series may exhibit infinite variance distributions, even in data of 100 years (e.g. the Dow). If an underlying distribution is not Gaussian and alpha is <2, *there is no population variance*. And if alpha is ≤1 there is no mean at the limit. In addition, the risk measure of standard deviation disappears (Peters, 1994).

Moreover, research on gold price and DJIA carried out (Small, 2005) showed that 'conditional heteroskedasticity' is not able to explain the structure observed in 'financial time series'. GARCH, when data exhibit deterministic components, is assumed to be stochastic, but is not. Moreover, when appropriate surrogate data and test statistics are chosen, there is strong evidence that the 'standard financial heteroskedastic models' (ARCH, GARCH, ARMA, EGARCH) are wrong. They do not offer an adequate description of reality. The markets are not genuinely efficient (Small and Tse, 2003).

When it comes to measure risk, industry's toolkit is indeed bare[38]. Economists use a key-variable to denote fat tails/kurtosis[39]: the alpha coefficient. Alpha appears in the characteristic function[40] of the L-stable formula[41] and its probability distribution. Normal distribution has $\alpha=2$ and skewness (β) = 0. Alpha also appears in Pareto's formula[42] (Peters, 1994). Daily 'Dow' had $\alpha=1.66$.

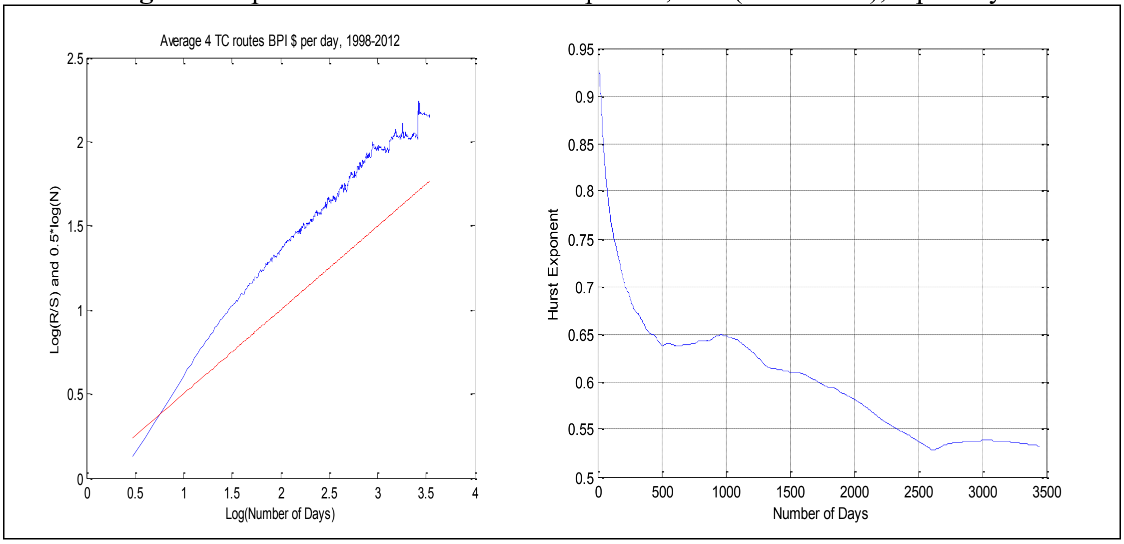
When $1\leq$alpha<2, variance becomes undefined or infinite, as mentioned (Peters, 1996); so sample *variance* is important information only in *random walk*. If the motion is not, variance is *little better than a meaningless measure of risk*. If $0<$alpha≤1 there is no stable mean; if $1<$alpha≤2, the mean is stable. Alphas in shipping markets *ranged between 1.38 and 1.56*, with a stable mean.

The H exponent measures price *dependence*[43] given by R/S = $(a*N)^n$ [1], (where n=H; $0\leq H\leq1$, N=the number of observations, a = a constant, H=Hurst exponent, and R/S = 'rescaled' range). [1] is more general than Einstein's for random walk (1905): Distance = square root of time [2]. When H=0.50, [1] reduces to [2]. Goulielmos (2009, 2010a) and Goulielmos and Psifia (2006) documented that freight rates observations are 'long-term dependent' with various values of H above 0.50 (e.g. 0.64+).

The H exponent [using NLTSA V.2.0 (2000) program and MATLAB 7.9], on data (from Clarkson's average 4 TC routes) for 'Baltic Panamax Index' (06/05/1998-16/02/2012), found 0.91 for $n\geq10$ (first logarithmic differences used to make data stationary). The benchmark for random walk is H=0.50, as mentioned, which represents normal distribution, and the independence of one freight rate change from next. The actual speed of a non-random freight rate time series is much higher, however, (Figure 6; left / blue line) from that of random walk (red line). Maximum H characterizes the whole time series.

[38] Another tool is 'beta'; it shows the correlation of a 'stock price' to 'changes in the general market'.
[39] S&P 500 showed, in daily variations (1970-2001), a kurtosis of 43.4>3; the October 1987 crash gave DJ 7.2; Nasdaq 5.8; 'CAC-40' 4.6 (rounded). Fama found that α for 'Alcoa', 'Standard Oil' and 'General Foods' was near 2 (normal) and near 1 for 'Westinghouse', 'United Aircraft' and 'American Tobacco'. However, the value of α depended on the *method* used to calculate it…
[40] Hudson-Mandelbrot (2004).
[41] A continuous, non-closed, form of probability distribution, unbounded up and down. Four parameters: the mean, the peakedness: $0<$alpha≤2, the skewness: $-1<\beta<1$ and the spread: $v>0$. The normal =alpha=2, skewness $\beta=0$ and v=1/2 of variance and = 2v. Characteristic function: $\log(f(t)) = i*\delta*t - \gamma*|\tau|^n*(1 + i*\beta*(t/|\tau|)*\tan(\alpha*\pi/2))$, where $n=\alpha$. For 'normal efficiency hypothesis' alpha= between 1 and 2. For EMH alpha = 2.
[42] $P(u) = (u/m)^n$ where $n= -\alpha$.
[43] Hudson and Mandelbrot (2004).

Figure 6: Speed of time series and H exponent, BPI (1998-2012), $ per day.



H=0.91 indicates that the 'time series of freight rates of the daily BPI' is persistent, trending in same direction[44]. This behavior is different from short-run Markovian[45] dependence. The non-parametric 'Rescaled range analysis' takes range (maximum value minus lowest value of time series) and divides it by (local) standard deviation, making it timeless and comparable over many decades.

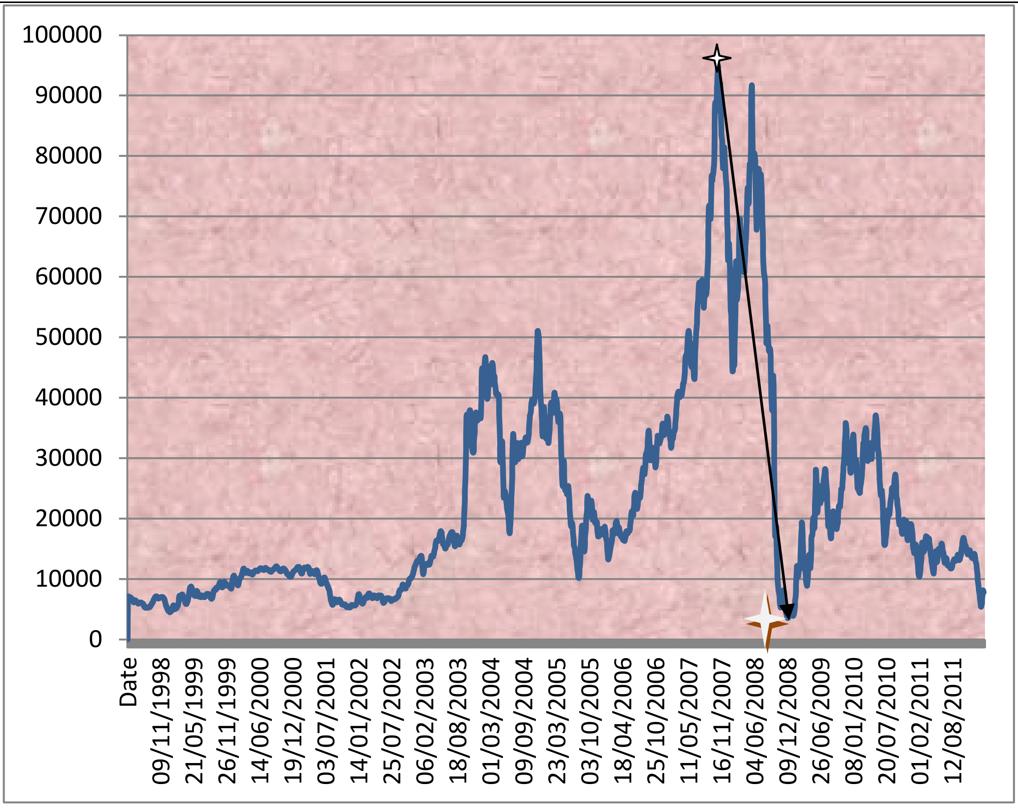
Important is that H is related to alpha[46]: H=1/α, establishing a dual (mathematical) relationship[47]. For H=0.91, *alpha is 1.10* (rounded), *indicating a severe discontinuity and a very wild and risky freight rate market, prone to wild freight rates swings*. In effect H and alpha embody two possibilities existing *in all time series*: 'Joseph' and 'Noah'[48]. The first shows *cycles and alternations of booms and depressions*, so familiar in shipping industry. Shipping industry is full of cycles lasting about 11 years on average[49]. A Noah Effect occurs when a *catastrophe comes*. Both effects are very close to real maritime life.

Figure 7 shows 'Panamax freight rate', which reached $95,000 per day, but suddenly fell to $3,500 in a time of 282 reporting days. Market suddenly and unexpectedly destroyed.

[44] For a fuller analysis about H (Steeb, 2008).
[45] Observations are dependent on previous observations in the short run.
[46] For proof (Peters, 1994).
[47] Hudson-Mandelbrot (2004).
[48] Names given by Mandelbrot on Bible's stories.
[49] Stopford (2009) counted 22 cycles since 1741, with an average trough of 6.8 years.

Figure 7: Average 4 TC routes for 'Baltic Panamax Index', $ per day (06/05/1998-16/02/2012).

$ Daily freight rates



Number of days. The Noah effect

The maximum freight rate occurred on 30/10/2007, and the minimum on 12/12/2008. Catastrophe lasted from end-2008 until 05/02/2009; re-appeared on 02/04/2009 until 14/04/2009. Rates were no higher than $10,000 per day. Considering a profitable rate of $30,000 per day and over, this appeared on and after 11/11/2009. So, catastrophe lasted 3 months. A 'Rainbow' appeared on the 11th November 2009. The cyclical character of shipping markets is (Goulielmos, 2009) also shown (Figure 7) with at least 3½ cycles of 1460 days each (20 reporting days = one calendar month). Data counts for a total of 172.5 months or 14.4 years.

7. The depression in shipping markets end-2008: what next?

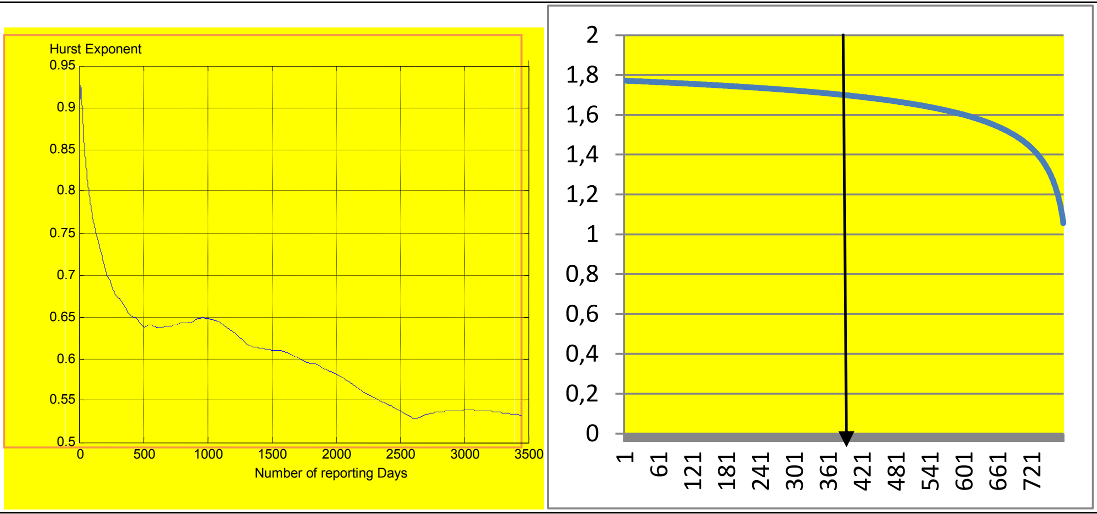
Figure 8 shows 2 effects: the 'Joseph Effect', indicating[50] (left) that BPI is a non-random time series; and the 'Noah Effect' (right), appeared in shipping on 12/12/2008, indicating the *catastrophe* in freight market with unprofitable record rates for at least 3 calendar months. Alpha = 1.1, which points out to a model specification of Cauchy[51] distribution with *fat tails* and *high peak in the mean*. Alpha for BPI = 1.88 for about 10 years and suddenly approached 1 (right; Figure 8).

[50] Indicates alternation of good and bad times.
[51] $F(x) = 1/\pi\,(1+x^n)$, where n=2, is the Cauchy's reduced probability density.

Figure 8:

H in BPI, 1998-2012 (Feb.). Alpha in BPI, 2008-2012 (Feb).

H Joseph effect	alpha Noah effect



Number of reporting Days (20/calendar month).

The low coefficient of alpha, 1.06, compared with alpha = 2 for normal, pretold the catastrophe in freight markets as indexed by BPI. Can we now predict Noah Effect and forecast the end the past prosperous shipping market? It is very important for ship-owners not to be taken by surprise by a depression, as this was done many times in the past.

Greeks, by optimism, but apparently irrationally in a depression, in 2009-2010-2011, obtained finance of \$68 and \$66b respectively, and paid \$6b in 2014 for 125 new-buildings; Greeks ordered 573 ships in 2011 in China and Korea. We reckon that it would be very beneficial to be able to predict depressions; so in what follows we will predict the precursors of the Noah effect, i.e. alpha - which indicates the Noah Effect (Peters, 1994; Hudson-Mandelbrot, 2006).

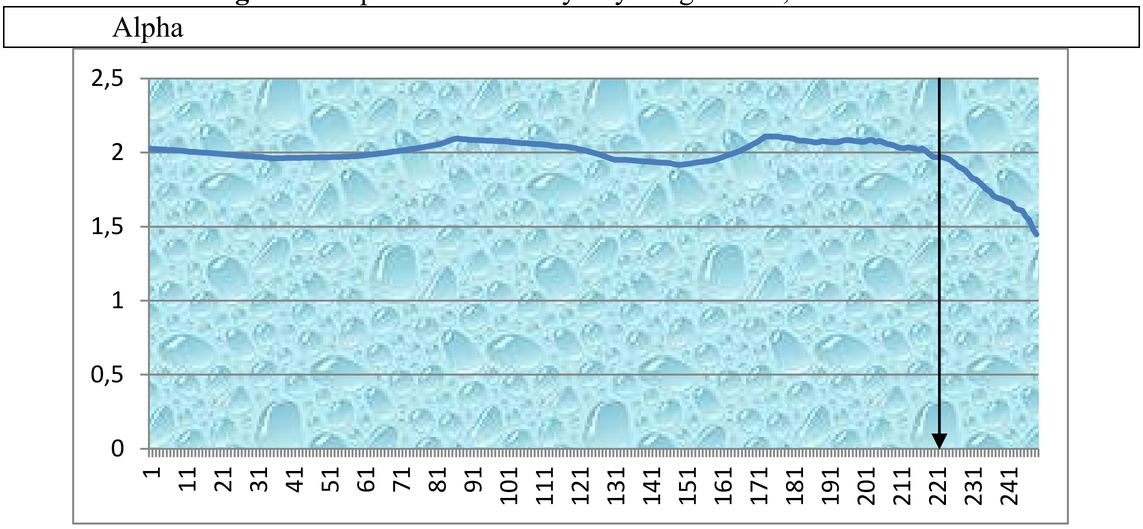
As shown (Figure 8, right), alpha started to decline sharply, from nearly 1.80, towards 1.06 (end 2008-start of 2012). It is recognized that a strong variation[52] of 'prices' is present, when alpha is 1.70 or less (Mandelbrot and Hudson, 2006). Using available observations (n=3450), we tried to forecast next 1-20 steps beyond February 16th, 2012, until 15th March 2012. This is a short run prediction, outside the sample, using the nonlinear 'Kernel Density Estimation' (due to Sugihara and May, 1990), giving rather good results. We obtained for one step ahead alpha 1.12 for mid March 2012; by 20 steps ahead alpha was 1.15. This means that a new catastrophe *is getting away from the present,* as alpha is improving[53].

The time series published by Stopford (2009) covers a very long period from 1741 to 2007[54] (259 years). This named 'Maritime Economics Freight Index' covering dry

[52] Alpha=1.70, following Hudson and Mandelbrot (2006), who recognized that this level of alpha indicates *strong variation* in prices (of cotton).
[53] Improved due to its approach to normal distribution's benchmark 2.
[54] Excluding missing statistics due to World War II (1939-1946: 8 years).

cargo market (Goulielmos, 2010b). Alphas for this series are plotted in Figure 9, using the formula alpha=1/H. The sharp downturn in the index is apparent after 221st year (1970), as alpha starts from a stable number 2 (=random benchmark) and ends at 1.45 (=2007). This indicates a very strong variation during the last 37 years (1971-2007). The freight market seems to have changed from random to deterministic, and from low risk to high! Those ship-owners that were in the market after 1971 (especially in 1973, 1975, 1981-1987 and end 2008-years of recessions and depressions) obviously had to be more capable than their predecessors in order to face increased risks.

Figure 9: Alphas of the Yearly Dry Cargo Index, 1741-2007.



Source: Data from Stopford.

Forecasting alpha, outside the sample, for next 5, 10, 15 and 20 years (using nonlinear 'Radial Basis Functions' due to Casdagli, 1989; this method too gives good results), we found the following values of alpha: 1.27; 1.15; 1.03 and 1.64[55]. These alphas indicate 3 periods of heightened risk: 2012-2016; 2017-2021 and 2022-2026. The period from 2022 to 2026 is very dangerous, as alpha is close to 1 = 1.03. For 2027 to 2031, alpha increases for the first time, from 1.03 to 1.64. This we consider as a risk reversal moving towards α=2. It seems that a new shipping depression, if it does not happen between 2002 and 2026, will probably not happen thereafter (Goulielmos et al, 2011).

8. Risk differs by the data used

Comparing the two time series used of a markedly different calendar time, (fourteen years vis-à-vis 259 years), we reached an important conclusion: *the degree of wildness/fatness of tails diminishes as you look at returns over longer and longer time-periods*. *Daily or weekly prices do not follow the standard model*. In short time frames prices vary *wildly*, and while at longer time frames, *start to settle down*. This was noticed by certain finance economists since 1963, but not by maritime economists. So, risk is a very deceptive concept, with many facets, depending also upon calendar time.

[55] Figures rounded to 2 decimals.

9. Conclusions

Risk, traditionally, used normal distribution, and it appears only in very rare extreme departures from the mean of a distribution, and par excellence beyond certain limit values of the standard deviation. This pre-assumes zero skewness and a kurtosis of 3. Time series, however, from real phenomena, like maritime freight rate indices, systematically and without any exception, shows excess kurtosis, excess skewness and normality rejection. It also exhibits serial correlation, preventing the application of diagnostic tests and causing misspecification in models used. Extreme events happen much more *frequently* than predicted by normal, and stock markets have a standard deviation changing from time to time, as recognized by GARCH and Turner and Weigel.

Modern finance, based on mathematics of Chance, tried to summarize risk using standard deviation and models based on 'random walk' and 'efficient market hypothesis', adopting also as a risk-measure 'beta'. This gave the message that in business life: 'the more you risk, the more you gain'. But risk is not only related to dispersion, despite the fact that this is supported also by chaos theory…

Alpha is mathematically related to Hurst exponent H and thus we could forecast the 'Noah Effect'. Moreover, as alpha diverges from 2, the correct specification of the model used here, changes the proper distribution from 'normal' towards 'Cauchy' (alpha=1; skewness= 0). The 'Panamax daily index' had an alpha 1.06. Moreover, the existence of 'Joseph Effect' not only indicates a market with ups and downs, but also long *term dependence* among observations. Forecasting, with 2 nonlinear techniques, indicated that a 'Noah Effect' -like that of end/2008- is not expected between now and 2031, with the danger to lie in wait for by 2027. It was shown, moreover, that the 'duration' of data used entails different risk for the same market and this was the reason for us to deal with daily data.

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