Modern Economy, 2018, 9, 1023-1044
http://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

# The Nature of Economic Turbulence: The Power Destructing Economies, with Application to Shipping

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**How to cite this paper:** Goulielmos, A.M. (2018) The Nature of Economic Turbulence: The Power Destructing Economies, with Application to Shipping. *Modern Economy*, **9**, 1023-1044.
https://doi.org/10.4236/me.2018.95066

**Received:** December 17, 2017
**Accepted:** May 20, 2018
**Published:** May 23, 2018



## Abstract

Studying the history of "economic turbulence", we ended up with the certainty that the statistical methods used so far, by economists, are unsuitable to model it. We have mainly the methods of Normal distribution and Random Walk in mind. Moreover, the picture of reality we get from time series depends on the time-frame of the data used… Different time-frame data, different reality… In addition, econometricians provided a whole family of econometric models to approach reality, starting in early 1980s, with "autoregressive models—AR" combined or not with MA (moving averages). But even its 1986 flagship, the GARCH, with its many variations, cannot cope with a number of characteristics, one of which is leptokurtosis (small alpha, higher peaks and long tails) [1], though some argue that it can cater for outliers. Economic turbulence, low or high—despite its characterization by Science as rare—became frequent since 1987 (Black Monday)... In late 1990s e.g. the global financial system underwent 6 crises—which have been called "near turbulences"—over a number of countries, including Russia in 1998. The next turbulence will not be one generation apart—we reckon. This paper is an attempt to invite writers to write a "theory of economic turbulence". Turbulence is a nightmare, which wakes people up suddenly, and unexpectedly, but it is something people wish to forget… till it strikes again: turbulence stroke in 1929 on (Black) Tuesday, then in 1987 on (Black) Monday and in end-2008, the Great Recession—on 29th September. In Black Monday stock markets around the world crashed losing a huge value in a matter of very short time (Hong Kong, Europe, and USA). The Dow fell ~23%. At that time OPEC collapsed in 1986 and the price of oil doubled… The dry cargo shipping sector entered a turbulent situation since 1989, which has been deteriorated since 2015 reaching finally an alpha equal to ~1.43 < 1.70 by 2035…

**Keywords**

Turbulences in Economics since 1885, Appropriate Distribution for Shipping since 1741, Turbulences in Stock Markets, Power Laws, Forecasting Turbulences to 2035, Nonlinear Forecasting, Alpha Coefficient

## 1. Introduction

Economies, and industrial sectors, suffered suddenly in the past from economic turbulences from time to time. In particular in the shipping sector, there were periods when ship owners made great fortunes and others when they became bankrupt [2].

The frequency of turbulences is related to the ability, which managers have now to take faster decisions, using more rapid computers and multi-service mobile phones. In addition, millions of people work now in the financial sector. After all, we all live in interconnected and globalized world-being citizens of one and the same village: the Globe.

In order not to be misled, computer models, are not yet in a position to cope with the rapidity that real economic life changes, as manifested in the situations when stock exchanges collapsed faster than computers, contrary to what was supposed by theory.

The "Economics of Turbulence" is now at the agenda given the meltdown[1] in end-2008, which reminded us of both the 1929 "Great Depression[2]" and the 1987 Black Monday, just ~21 years ago. USA's annual real GDP during 1929-1934 fell from \$1000 b (constant 2005\$) to \$700 b (−30%) and recovered by 1938-1939 to \$1000 b again (1910 = \$550 b). Additional depressions have been recorded in 1819, in 1873-1896, in 1907, and in 1910-1911. Another Black Monday was the 09/05/1873 for Vienna stock exchange, and the "Long Depression" that followed.

Should the models based on normal distribution forecast turbulence? Normal distribution—as shown in **Figure 1** excludes… turbulences. Turbulence is the manifestation of forces, which cause standard deviation-$\sigma$-to escape beyond ±3 from its mean... People are by now familiar with the fact that plethora of $\sigma$'s occurred beyond ±3… (**Figure 13**). Moreover, evidence is accumulated by now against "random walk hypothesis" [3] [4].

As shown, 68.2% of all outcomes are within $\pm 1\sigma$ from mean $\mu$, 95.4% are within $\pm 2\sigma$ and 99.6% are within $\pm 3\sigma$. Beyond $\pm 3\sigma$, the probability of an outcome to be there is between ±0.2% and ±0.4%: points at which distribution curve touches zero.

[1]Dow Jones Industrial Average fell 7%; in few hours more than \$1.6 tr. was wiped off the value of USA industry and \$5tr. globally.

[2]This term is frequently attributed to economist Lionel Robbins (1898-1984) Professor at LSE due to his 1934 book "The Great Depression". A depression in economics is the same as turbulence (in Physics).

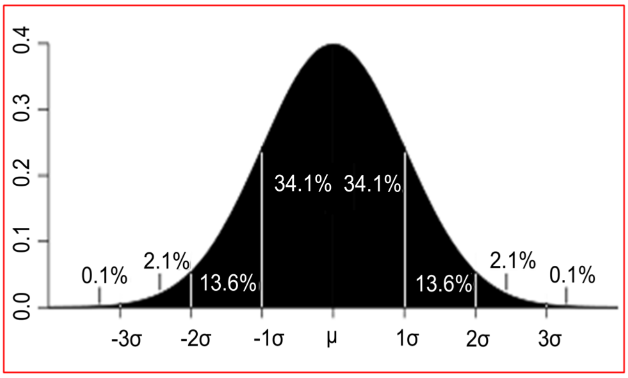



**Figure 1.** Normal distribution and the approximate areas beneath it, and their relation to $\sigma$. Source: internet site on normal distribution.

In addition to the reliance on normal distribution, science has relied on models of 1) "classical linear regression", 2) "ARMA"(autoregressive moving average models) and 3) "VAR" (multivariate time series with lagged values on right hand side), which are linear in nature, *i.e.* linear in parameters: $Y = X\beta + u_t$, where $u_t \sim N(0, \sigma^2)$, where "errors" follow normal distribution with mean 0 and variance $\sigma^2$ [1].

Many relationships in finance, and shipping, are intrinsically non-linear [4]. Linear structural models and time series are unable to explain a number of important features, common to financial, and shipping, data: 1) leptokurtosis, meaning fat tails, and excess peaks at the mean; 2) volatility clustering/volatility pooling, meaning that volatility appears in bunches: *i.e.* large returns follow large returns, and small returns follow small returns. Some relate this to the way information arrives; 3) the leverage effects, meaning that volatility rises more following a large price fall, than a rise of the same magnitude [1].

## 2. Aim and Organization of the Paper

This paper aims at looking on "economic turbulence", which shipping and financial time series exhibit at occasions. Also, a method to forecast turbulence in the shipping sector for 20 years to come is used, outside the sample, *i.e.* for 2016-2035 using the nonlinear method—the "Kernel density estimation".

The paper is organized as follows: next, is a literature review, followed by methodology. Then, the concepts of volatility, risk and uncertainty are presented. Next, the more suitable method to model economic turbulences is indicated. The "maritime economics freight index" is then presented. Next, the phenomenon of power-laws in stock exchanges is analyzed, and the meaning of coefficient alpha is given. Finally, we forecast the turbulences that we expect to appear in shipping sector till 2035, and finally conclude.

## 3. Literature Review

Ruelle and Takens [5] defined mathematically turbulence (in physical systems) as follows: let a physical system consisting of a viscous fluid, and rigid bodies, to be subject to a zero external action—and let this action measured by a parameter $\mu$. If $\mu = 0$, the system now tends to equilibrium. Next, submit the system to a "steady, light, positive, action" $\mu > 0$, thus obtaining a steady state (the physical parameters of the fluid are constant); this fluid is in dis-equilibrium. Let assume now $\mu > 0$, and increasing: then 1) the fluid will have a change in its symmetry pattern, 2) a periodicity in time, and 3) given a sufficiently large $\mu$, its motion will become very complicated, irregular and chaotic: this is turbulence.

Feynman [6] has described turbulence as the most important, but unsolved problem of classical physics. Turbulence has the following features: irregularity (highly)—with a lengthy scale; chaotic always; diffusive; rotational; dissipative; energy cascading; with integral length scales and with Kolmogorov ones as well Taylor's microscales…

Mello [7] argued that "natural catastrophes" are extreme events, possessing—(at times)—an infinitesimal likelihood to occur... In statistics, extreme events occur on "the tails" of a probability distribution. He suggests the use of (fat-tailed) statistical methods coming under the broad scope of "Levy[3] processes" [4] [8].

The scientific community, Mello [7] argued, came to rely over-abundantly on Normal distribution. There is an urgent necessity to explore the notion that other processes may be better suited for determining probability estimates for extreme events (*i.e.* events that result to turbulence) (italics and bold added). He showed that H (the Hurst exponent defined in methodology) falls between 0 and 1, and alpha = 1/H is >2; the fractal dimension of the path cannot, however, exceed its Euclidean dimension 2.

Anonymous [9] introduced a statistical model based on the class of "*symmetrica*-alpha stable distributions", which are well-suited for describing signals that are impulsive in nature: $\varphi(\omega) = \exp\left(j\delta\omega - \gamma|\omega|^{\alpha}\right)$, where alpha is the characteristic exponent restricted to 0 < alpha ≤ 2, delta ($-\infty < \delta < \infty$) is the location parameter and $\gamma$ (>0) stands for variance. When $\alpha$ is in the interval [1-2], then delta = the mean of the distribution; when 0 < alpha ≤ 1, delta = median, as the mean is undefined. The shape of one "standard alpha-stable density function" is shown in **Figure 2**; we have chosen there alpha = ½ on purpose to show the high peak and the long tails involved.

As shown, the peak of the distribution (alpha = 1/2) is, at $f(x) = 0.65$, at a higher height than if alpha was = 1, 1.5 or 2. This is the impact of alpha on the peak of the distribution, producing also fat tails, or long tails, beyond $\pm 5\sigma$.

Mandelbrot and Hudson [4] argued that financial turbulence is not rare. Turbulence is at the heart of markets, where the key phenomena are: wild price swings, business failures, and windfall trading profits. Mitigation is needed with focus on the concentrated bursts of action and the discontinuities in prices,

[3]Levy P. was one of the greatest scientists of probability, writing in 1937. He invented the "stable" probability distributions: their basic properties remain unaltered by rotation, shrinkage, or addition: like Gaussian and Cauchy. These are called "L-stable" by Mandelbrot. One of their characteristic function—in logs—is: $\log f(t) = i*\delta*t - |c*t|^{\alpha}*\left(1 - i*\beta*\left(t/|t|\right)\right)*\tan(\pi*\alpha/2)$, if alpha ≠ 1.

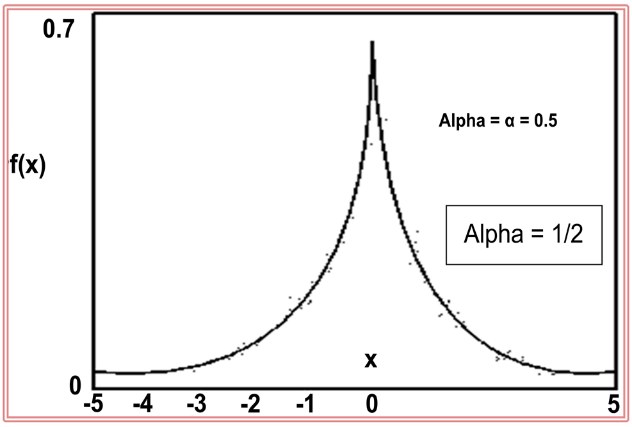



**Figure 2.** A standard symmetric stable-alpha distribution density with alpha = 0.5. Source: Inspired by anonymous [9].

events that common economic wisdom says should not happen and calls them "statistical outliers". The assumptions underlying models are wrong. Standard financial models focus on a typical market behavior, *i.e.* modest price changes, real or seeming trends, a risky, but ultimately closely manageable world. Risk = $\pm 3\sigma$. For shipping this means ±308 units of the shipping index (**Figure 12**; 1947 = 100), where $\sigma = \sim 103$. The index had 42 units in 1972 min. and 795 in 1918 maximum.

Trevethan and Chanson [10] argued that turbulence is not Gaussian, particularly in Nature. Any turbulent flow is often dominated by coherent structure activities and turbulent events, meaning a series of fluctuations that contain more energy than average ones.

Juarez [11] used a "complex"[4] model, applied in "weather forecasting" by the meteorologist Lorenz [12] in 1963 (**Figure 3**), known as the "wings of the butterfly" or "the eyes of owl", to determine the relationship among: cash flow, profit & loss and assets of 70 companies in the crude oil mining and natural gas in Colombia.

When Juarez used conventional methods the explained variance was 6%, but after certain dynamic transformations he made, he succeeded to increase that to 73%, fitting a linear regression (**Figure 4**).

As shown, the dependent variable is the "profit & loss $X$", and the independent variables are: "cash flow $Y$" and "assets $Z$". This model resulted in a better prediction, as argued.

Zou *et al.* [14] argued that the financial time series of prices, deviated significantly from "standard normal", and had nonlinear data characteristics. Skewness of −0.0273 and kurtosis of 7.1647 for 1790 days[5] (02/01/2002-13/02/2009)—deviated from "normal" levels (kurtosis = 3; skewness 0). This indicates that the market exhibits significant abnormal return changes. The null hypothesis of "Jarque-Bera" "test of normality" and "BDS" "test of independence", were both

[4]These are: $dx/dt = -10x + 10y$, $dy/dt = -xz + 28x - y$ and $dz/dt = xy - 8/3\,z$.

[5]Observations concern "the US West Taxes Intermediate (WTI) of crude oil".

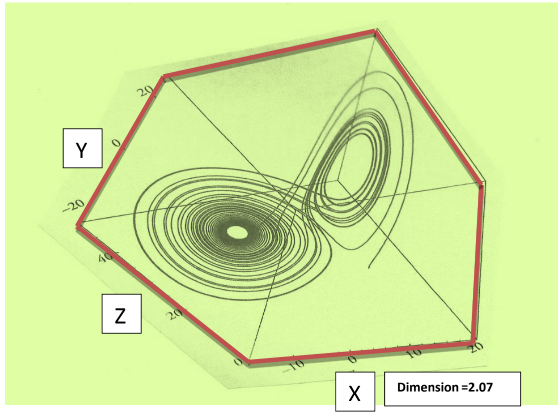



Figure 3. Chaos in the form of a strange Attractor for Weather forecasting due to Lorenz (1963) [13].

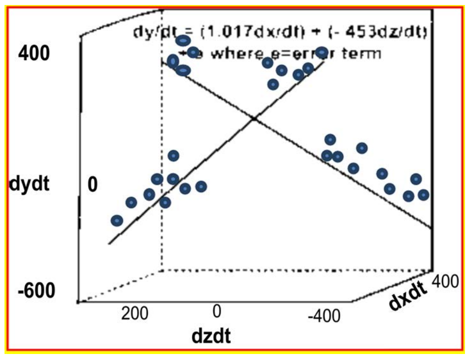



Figure 4. Cash flow, assets and profit & loss of 70 companies of crude oil mining and natural gas in Colombia using a Lorenz model of 3 nonlinear differential equations for weather forecasting. Source: Inspired from Juarez [11].

rejected. This means that market returns contain unknown nonlinear dynamics, not easily captured by traditional linear models (italics added).

In summary, we showed, among other things, that turbulences are considered in a probabilistic manner, as rare economic phenomena. This, however, we doubt; looking at Black Monday, 1987, and at the Great Recession, in end-2008, there were only 21 years apart... Turbulences are also always chaotic and are expressed exclusively by the "Levy stable distributions". Alpha < 2 creates fat tails and high peaks, a serious number of outliers and thus unexpected outcomes (turbulences).

## 4. Methodology

First, we distinguish volatility/turbulence in 3 states: 1) when volatility is mild, and modelled by Normal distribution, and $\sigma \le \pm 3$. 2) When turbulence is modelled by an "in -between" distribution, and turbulence = alpha = 1.5 ≤ 1.70 and $\sigma > \pm 3 \le \pm 12.99$. This is a representation of the shipping sector. 3) When turbulence is modelled by a Cauchy distribution, being wild, and alpha = 1 and $\sigma \ge \pm 13$.

We assume also that shipping time series behave like financial ones [15]. This assumption entitles us here to construct bridges between finance and shipping. For shipping a cause of turbulence is a serious dis-equilibrium between demand and supply, as argued by Koopmans [16].

The relationship between Hurst exponent and alpha coefficient: Let $R_n$ be the sum of a stable variable in a particular interval n, and $R_1$ be its initial value, then [8]:

$$R_n = R_1 * n^{1/\text{alpha}} \tag{1}$$

means that the sum of n values scales by $n^{1/\text{alpha}}$ times their initial value. Taking logs:

$$\text{alpha} = \log(n)/\log(R_n) - \log(R_1) = \log(n)/og(R/S)l = 1/H \tag{2}$$

where

$$H = \log(c) + \log(R/S_n)/\log n \tag{3}$$

where log(c) = 0 being constant.

$$\log R_n - R_1 \sim R/S \text{ and thus alpha} = 1/H \tag{4}$$

Equation (3) has been developed by Hurst [17] to determine long-memory effects and a fractional Brownian motion, using the range of a time series divided by local standard deviation ($R/S_n$); also

$$(R/S)_n = c \times n^H \tag{5}$$

(Rescaled) range is a method dealing with volatility rescaled to make it independent of time. It is a generalized method to measure the speed of a time series including the case of Einstein 1905 [18] as a special one. Einstein [18] proved that a particle (and assume also a time series) moves at the square root of time n, *i.e.*

$$\text{Distance} = \sqrt{n} \tag{6}$$

$n$ stands for the number of observations or of time steps. With $H = 0.69$ (rounded) there is "black noise" in shipping markets, which is characterized by catastrophes and discontinuities, which are abrupt up and down, indicating high peaks at the mean and fat tails…

In forecasting, we used the "Kernel Density Estimation" method—KDE. It is slightly simpler than the other local linear forecasting methods, being in fact a weighted average. We used this method successfully in other occasions [19] [20]. The forecasts are given by

$$X_{(N+1)\text{prediction}} = \sum_{i=1}^{k} WjXj + p + (m-1)T \tag{7}$$

where—if possible—

$$\Sigma W_i = 1. \quad W_i = f(R_i)/\Sigma f(R_j) \tag{8}$$

where j = 1 to $k$. $R_j$ are the distances to which a weight $f(R_i)$ is

$$\text{attached} = \exp\{-R^2_i/c^2\} \tag{9}$$

where c is the mean of $R_i$. For the last point $X_T$ (bolds stand for vectors), we select the $k$ nearest neighbors $X_j$, where

$$j = 1(1)k \tag{10}$$

and m stands for embedding dimension, the time delay is $T$, k is the number of the nearest neighbors and $p = T - k$. This method is due to Sugihara and May [21] with k = m + 1 and $x_\tau$ are included in $x_j$. Forecasting is based on the mean of the relocated points weighted, as far as the initial distance is concerned.

## 5. The Concepts of Volatility, Risk and Uncertainty

Business life—blackboard theorizing, and uncountable conferences—became familiar with the concepts of risk, volatility and uncertainty. Companies need help and effective ways of their protection from these three enemies (*i.e.* use of hedging). As a result, managers may easily become victims, where the "Sirens" are in the form of all kinds of derivatives.

Is volatility = turbulence?

The $\sigma^2$ measures the spread of data round mean:

$$S(n) = \left\{ 1/n \sum_{n=0}^{n-1} \left( u_n - (u)_n \right)^2 \right\}^{1/2}, \tag{11}$$

where $u_t$ stands for discrete time series, $(u)_n$ stands for the mean over time lag n; $\sqrt{\sigma^2} = \sigma$ [22]. Moreover, adaptive models for (mild) volatility have already created by econometricians: ARCH, GARCH 1986, EGARCH, and GJR[6] 1993 etc. Volatility (mild) in addition is not disastrous. e.g. an earthquake at a low point on Richter's climax causes volatility, but not devastation. Tsunamis, hurricanes, the Katrina, the Caroline, are different. Volatility[7] is like a severe fever… to put it simply, and a broader concept of turbulence.

For econometricians, volatility is the degree to which a time series varies over time. It is usually measured by variance[8], denoted by the Greek letter $\sigma^2$. In finance, $\sigma^2$ is often also used as a measure of risk[9]. Risk[10] is very important for companies; firms wish to manage, avoid or profit from it. Moreover, $\sigma^2$ appears

[6]A model due to Glosten, Jaganathan and Runkle (GJR) to allow for asymmetries in the relationship between time varying volatilities and returns of different signs, Journal of finance, 48, 5, pp. 1779-1801.

[7]As reported by Mandelbrot and Hudson (2006 [3], p. 276), the Dutch had 1,800 dead people in 01/02/1953 (and in 1570) due to a very bad storm dismantling the sea dikes in Amsterdam, built on the basis of "normals". The flood was 3.85 meters higher, meaning 0.0001 odds, but it happened twice.

[8]To calculate variance: find the mean of the returns (of a security over a given period) (=the expected return); subtract this from actual (=deviation from mean). Square this in each period, and take averages (=the variance of the returns of the asset). The larger the variance, the greater the risk…

[9]Risk is associated with the price-fluctuations of a given asset (or stocks, bonds, property, etc.), or the risk of a portfolio of assets (mutual funds, index mutual funds, or ETFs). Risk determines also how efficiently one manages a portfolio of investments, determining the variation in returns on the asset and/or portfolio, and gives investors a mathematical basis for their investment decisions (="mean-variance optimization").

[10]It is believed that if risk increases, the expected return on an investment should increase, (="risk premium"). When evaluating investments, investors should estimate both expected return and "uncertainty" of future returns (=standard deviation: a quantified estimate of uncertainty too).

in the equation of normal distribution, and the probability of the risk of a decision is locked in $\pm 3\sigma$ from mean… maximum, as mentioned.

Let us present volatility in shipping markets (**Figure 5** and **Figure 6**).
As shown (left), all 3 main ship sizes and markets had strong variations in their earnings since 2011; par excellence Capes[11] (blue line) had for the first time in 2012 hires (=time charters), which fell from >$42,350 per day to $2,350 (!), as well in 2016. The "BDI-Baltic Dry Index" (right) fell from a high of ~11,800 units in 2008 to ~400 by 2015. Capes were heavily involved in China's imports in serious volumes.

## 6. Which Is the More Suitable Method to Model Economic Turbulence?

Shipping and Finance cannot be modeled by Normal distribution... due to the alpha they have [20]. They are better modelled by a type of distribution, where alpha is 1.50, called "Fractal or Pareto". What is alpha? Alpha is the new indicator of risk, of uncertainty and volatility for leptokurtic distributions. **Figure 7** shows the values of "shipping" alpha—starting with 1.70 and ending to 1.47 for shipping dry cargo markets from 2003 to 2015. Alpha = 1.70 as the upper benchmark of a strong market variation as indirectly "defined" by late Mandelbrot [4].

**Figure 8** presents the 3 known graphs of 3 well known distributions: normal, Cauchy and Financial/Shipping. The only difference is the value of alpha, which creates longer tails and higher peaks as the case may be. Let us see the main distributions closer.

Normal distribution

The equation of normal[12] distribution (**Figure 9**) is:

$$f\ (x) = 1/\sigma\sqrt{2}\pi * e^{-((x-\mu)/\sigma)2/2} \tag{12}$$

where $x$ is the level of a specific variable under study, $\mu$ is the average value of all $x$'s round average, $\sigma$ stands for standard deviation—and $e$ is a constant[13].

As shown, the tails approach zero at $\pm 3.5\sigma$ from mean[14] ($X = 0$).

### 6.1. The Rationale behind Normal Distribution

Normal distribution is the statistical expression of "human justice", which indicates that there is an "equal" return for everyone (egalitarianism). "Normal" distribution describes a world of mild circumstances. Normal markets are fair... Normality also means that all price changes taken together from small to large vary in accordance with the mild, bell-curve, distribution. What about if data

[11]Ships as large as to be able to pass Panama Canal via the Cape of Good Hope; these are round 200,000 + dwt.

[12] $f\left(\text{Gaussian}\right)$ can be also $= 1/\sqrt{4}\,\pi\gamma * \exp\ \left[-\left(x - \delta\right)^2/4\gamma\right]$, if alpha is between 1 and 2.

[13] $e$ is an irrational number with infinitely non-recurring digits starting as 2.7182.

[14]The "reduced" normal distribution is when $\sigma = 1$ and $\mu = 0$. Also, if we want to know how many σ from the average value is each $x$: $z = x_i - x_{\text{mean}}/\sigma$ {2}.

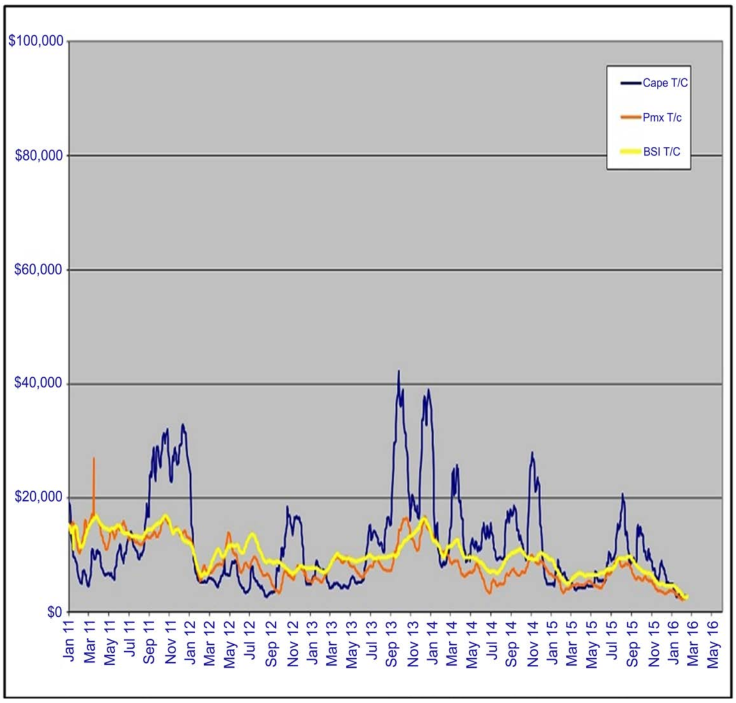



**Figure 5.** Time charters in $ for Cape, Panamax and BSI (handy) ships, 2011-2016 (March).

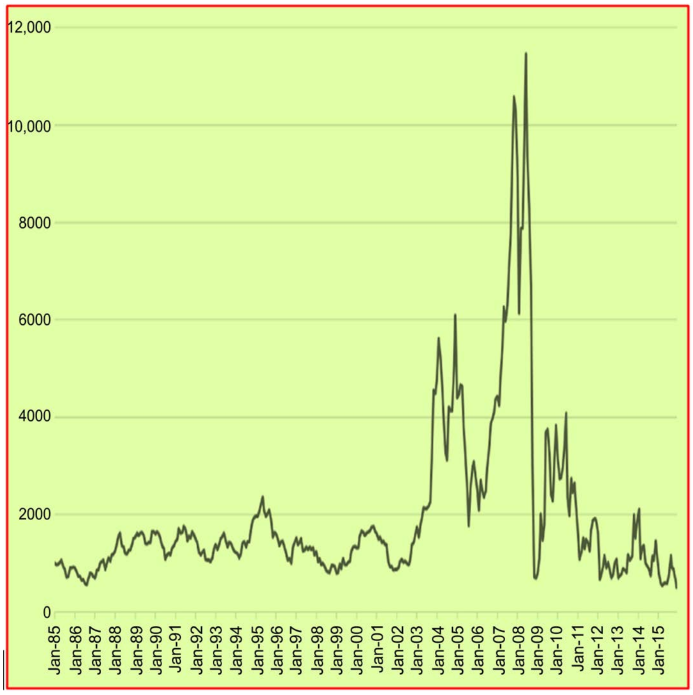



**Figure 6.** Baltic Dry Index, 1985-2015. Source: Baltic Exchange UK, and various brokers.

show that the magnitude of price changes depends on those of the past? Can markets exhibit dependence without correlation? Can large price changes tend to be followed by more large changes, + or –, and vice versa? Is volatility clustering?

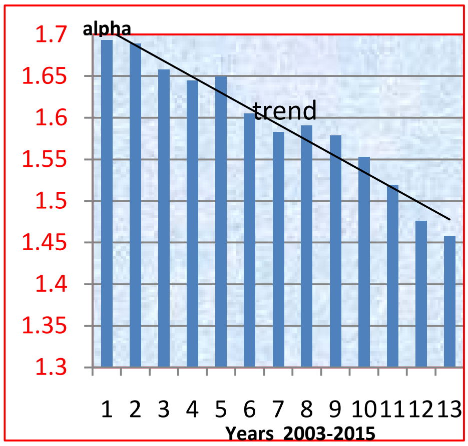



Figure 7. Alpha coefficient in shipping (dry-cargo) distribution, 2003-2015. Source: Data from [3] using "Rescale range" method and excel, given that 1/H = alpha.

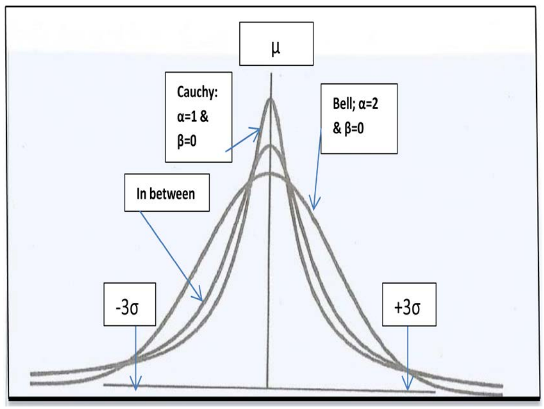



Figure 8. Three different alphas and the resulting shape of distributions. Inspired by [4].

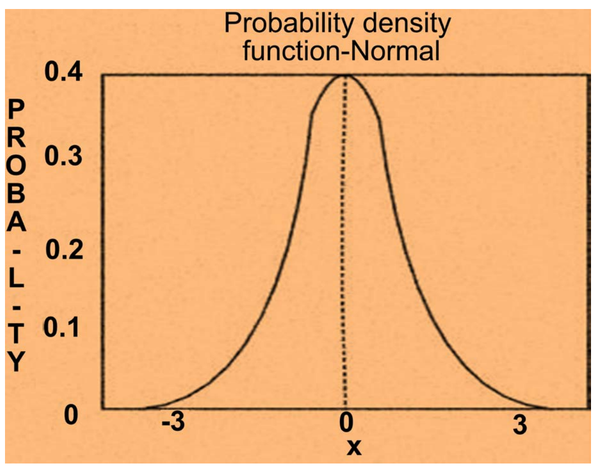



Figure 9. The Normal Probability density function. Source: Inspired by Mello [7].

## 6.2. The Inadequacy of Normal Distribution

For some time, and especially since 1987, evidence showed that normal distribution is not adequate at times to describe market returns, and thus a need arises to

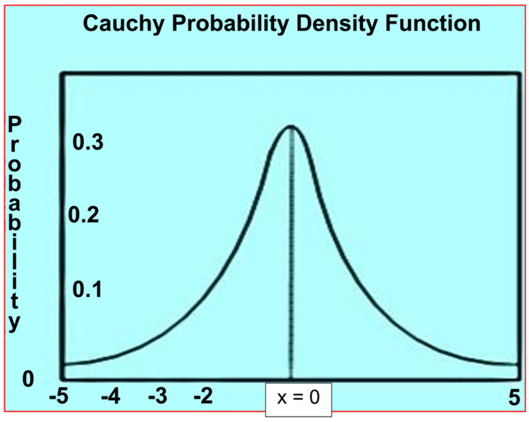



**Figure 10.** $f(x) = 1/\pi(1 + x^2)$: the reduced Cauchy probability density[15]. Source: Inspired by Mello [7].

replace it. We know that there are cases where amplifications occur at extreme values, and often we have a long-tailed distribution.

### 6.3. The Cauchy Probability Density Function

As shown (**Figure 10**), Cauchy distribution is a curve with fat tails; the curve is not close to zero even at $\pm 5\sigma$… Alpha is 1 and thus the peak is higher than "normal's and Pareto's" peaks. This indicates the higher probabilities that exist on the tails. This also means that when volatility/risk increases beyond $\pm 3\sigma$, the Cauchy distribution is more reliable. Remember the 22 "standard deviations" by which "Dow Jones I. A." in 1987 (Black Monday) departed from mean [4].

### 6.4. The Levy Distributions

The long-tailed distributions led Levy (1937) to formulate a "generalized density function", where "Normal" (and "Cauchy") distribution are special cases, using a generalized "Central Limit Theorem[16]". These distributions—called "stable Levy distributions—SLDs"—are useful in describing the statistical properties of turbulent flows.

One characteristic function of an SLD is:

$$\log f(t) = i\delta t - \gamma |t|^{\alpha} \left[1 + i\beta(t/|t|)\tan(\alpha\pi/2)\right] \tag{13}$$

[4]. This function has 4 parameters: the location parameter delta, $\delta$ (~mean); the scale parameter, $\gamma$; the skewness $\beta$ (if 0, the curve is symmetrical) and the most important coefficient alpha, $\alpha$—which determines the fatness of the tails (if = 2, the distribution is normal). If alpha = 1 and $\beta$[17] = 0, these stand for Cauchy distribution, and if alpha = 1.50 and $\beta \neq 0$, these stand for "shipping and finance

[15] Also $f(x) = 1/\pi \times \gamma/\gamma^2 + (x - \delta)^2$, if alpha takes values 1 and 2.

[16] This is the law of large numbers arguing that a sample of independent and identically distributed random numbers approaching $\infty$, its probability density function approaches normal distribution. Alpha equals 2 and Hurst exponent = 0.50. The "generalized central limit theorem" states that the family of stable distributions contains all limiting distributions of sums of i.i.d. random variables.

[17] $-1 \le \beta \le +1$ for skewness. Symmetry needs $\beta = 0$.

distributions", as well as Pareto's distribution. Alpha takes values from 0 to 2, with variance $2 \times \gamma^2$, and for shipping and finance alpha takes values from 1 to 1.7.

A proper model for turbulence is the one which allows: wild price fluctuations-big jumps, fat tails (alpha < 2), volatility clustering—here and there—periods of big price changes, grouping together, interspersed by intervals of more calm variation—long memory and persistence ($H > 0.5 \leq 1$), and scaling of price series.

## 7. The "Maritime Economics Freight Index", 1741-2015

The time series of "maritime economics freight index", 1741-2007 (extended to 2015) [2] is shown (**Figure 11**), with its "normal distribution" (**Figure 12**).

As shown, the shipping distribution—fitted to 266 years—exhibits a positive skew, and is not normal. The skew is positive and greater than zero[18]. More important is that the fitted distribution indicates a long tail on the right, and peak at ~144 units, which are measured by alpha—mentioned below—equal to 1.46 < 2. The shipping standard deviation went away from its mean by $6.52\sigma$ in 2008…

Turbulences/volatility in shipping historically is as follows: In class I, recorded none. In class II recorded none too. In class III were recorded 14 cases: in 1916 3.8; 1917 7.1; 1918 $7.7\sigma$; 1919 5; 1920 $3.8\sigma$; 2004 $3.4\sigma$; 2007 5.7; 2008 $6.5\sigma$; 2009 3.6; 2010 4.5; 2011 3.9; 2012 3.4; 2013 3.3 and in 2014 $\sigma = 3.1$.

The dry cargo market held up till 1974 and for small bulk carriers into 1975. There was stock building in the world economy due to commodity price inflation and the heavy congestion in Middle East and Nigeria due to increased oil revenue [2]. The spot market moved into recession in 1975 till 1978. The sector entered into a deep depression in 2nd half in 1981 till 1st half in 1987. Stock markets are, however, wilder.

## 8. Turbulence in Stock Markets

**Figure 13** gives a concise picture of turbulences since 1885. It shows that serious turbulences in stock prices are discontinuous. Obviously, a depression is the main cause of an economic turbulence. The four most serious turbulences, since 1885, were in: 1) 1894, 2) 1929, 3) 1987 and 4) end-2008, measured by changes in $\sigma$ of monthly stock returns. These reached the maximum change in $\sigma$ of ~+25%.

**Figure 13** records ~48,000 days-1572 months of stock returns (1885-2016). Stock market exhibited about 15 incidents of serious economic turbulence, *i.e.* above 13% change in $\sigma$, since 1885. Deviations above 7.5% changes in $\sigma$ were fewer—about 45—while hundreds can be found between changes in $\sigma$ of 1% and up to3% (not shown)—the benchmark of normal distribution—and fewer between 3% changes in $\sigma$ and 7.49%. The great number of turbulences 54.5%, indicated by changes in $\sigma$ ranged from 1% to 8%; about 1/3 = 34%= of the 132 or

[18]The "Pearson coefficient of skewness" = 3(mean-median)/(standard deviation) = 3(143.63977-116)/102.735746) = 0.81 rounded > 0; $-1 \leq$ skew coefficient= $\beta \leq 1$.

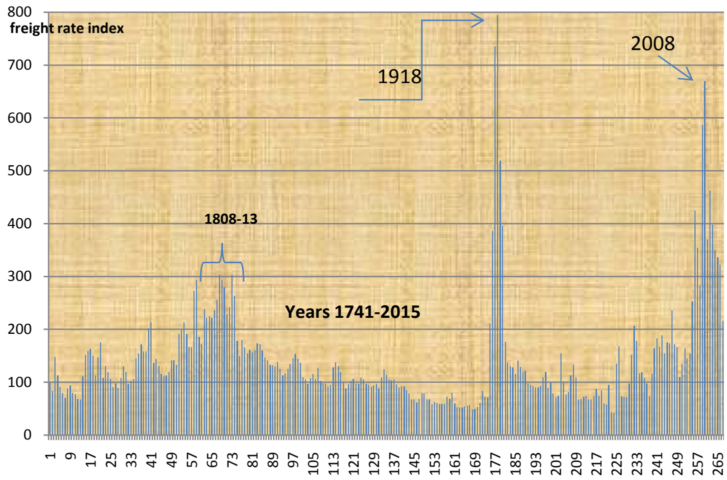



**Figure 11.** The freight rates index of dry cargo, 1741-2015 (1741 = 100 = 1947). Data: from Stopford [2], 1741 till 2007; from Clarkson's staff: 2008-2015; data for 1939-1946 (8 years) are missing: 275 years − 8 = 267 − 1 for stationarity = 266.

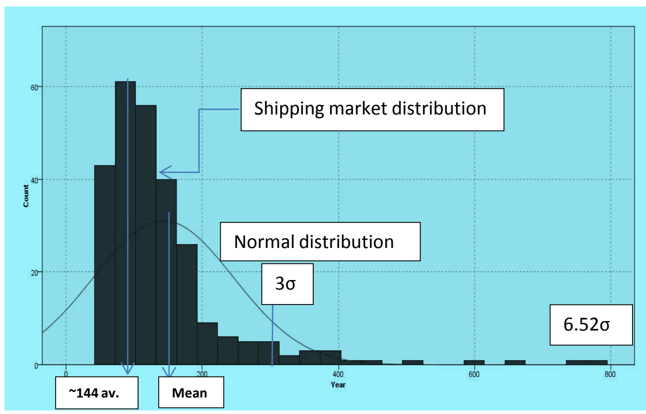



**Figure 12.** Maritime economics freight index distribution, 1741-2015, vis-à-vis its normal distribution (1741 = 100 = 1947). Source: Data as in **Figure 9**; SPSS web report; extreme values = 10; Skew: 3.197 > 0; kurtosis 13.66 > 3.

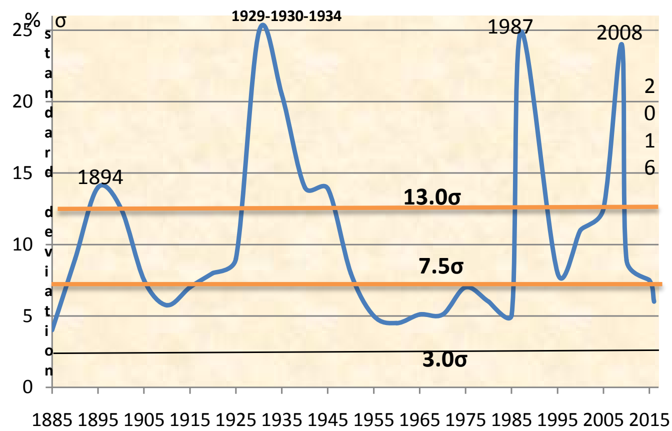



**Figure 13.** A history of Volatility in Stock markets: 1885-2016, (changes in σ of the monthly stock returns from daily returns in the month). Source: Data from Schwert, G William [23], http://schert.simon.rochester.edu/volatility.htm plus excel.

so years (~45 years) showed turbulences from 9% to 14% and the rest 15 years (12.5%), showed turbulences from 15% to ~25%.

Turbulence, though studied for more than 100 years, is only partly understood by theory [4]. Why are markets turbulent? **Exogenous** factors are to blame [4][19], as called by economists and econometricians. Also, the size of firms and industry's concentration influence profits, and in turn profits determine stock prices.

The key traits of turbulence are: "scaling"-$\gamma$ and "long-term dependence"—or a Hurst exponent $H > 0.5 \leq 1$. Also, "self-similarity" is a property of invariance against changes in scale or size. Small parts of an object are qualitatively the same—or similar—to the whole [8]. This underlies fractals, chaos and power laws. This further means a decisive symmetry. Symmetry means that matters are the same, *i.e.* they are invariant in change: or something stays the same, in spite of alterations [24]. The characteristics of economic turbulence are: abrupt lurches between wild motion and quite activity; discontinuities; intermittency; and uncertainty about major events in time [4].

Economic history is also full of "near"[20]—turbulent events—like that of October 27th, 1997. The Dow then lost a 7.2%; cascades of selling occurred across exchange—forcing authorities to halt trading in 2 times [4], affecting 1 billion shares. This turmoil spread round the globe stock exchanges: Hong Kong—14%; London—9%. The value of USA business fell at a rate of $100 m per second! The study of roughness, of the irregular and of jagged (turbulence) is needed.

## 9. Stock Exchange: The House of Power-Laws

The place where chaos[21] reigns over charts is Wall Street. In stock and commodity exchanges, "self-similarity" weighs in on many scales. The paradox here is that the chart of minute-by-minute stock averages looks much alike the daily averages and so on in weekly, and in monthly prices… There is an uncharacteristic jump in the data—as in October 1987 as shown in **Figure 13** [24]. Such price jumps are also known as "innovation processes".

The "linear" (normality) assumption is that in stock averages the actual prices are generated by independent increments. This has a power spectrum that is proportional to the inverse square of the frequency, called "brown noise", as an allusion to "Brownian motion". The name of this motion is after the Scottish botanist Robert Brown (1773-1858), who in 1827 saw floating dust specks to "move" in a microscope. The innovation process consists of the independent "kicks" given to the suspended particles by the molecules of the liquid (in which they float/hover).

### Pareto's Power Law

Pareto (1848-1923) was an industrialist, economist and sociologist. The field of

[19]An exogenous variable is an explanatory variable not appearing as a dependent variable, but it plays a role in the determination of the values of endogenous variables.

[20]We say "near" having in mind the 1987 stock markets around the world crash, where DJIA fell ~23%.

[21]This is a deterministic, nonlinear, dynamic system that can produce random-looking results. It has a fractal (non-integer) dimension and must exhibit sensitive dependence on initial conditions.

economics evolved by his efforts from a branch of social philosophy—as practiced by Adam Smith (1723-1790)—into a data—intensive field of scientific research and mathematical equations. He attracted by the way "power" and "wealth" is distributed. He gathered extensive data from 1471 to 1512, and plotted them (in 1909) on a graph (**Figure 14**): income level is measured on vertical axis, and the number of people having that income, on horizontal. The result was that very far in the bottom was the mass of people and very thin at the top was the wealthy elite. Pareto proved that few people are extremely rich and the great masses are poorer.

As shown, the curve is not symmetrical. The slope of the Pareto curve—alpha—is equal to −3/2 = −1.5 (power law)… Money begets money, power creates power. "The first 1/2 a million $ is difficult, while the $1 m is easier thereafter" or "increasing returns to scale", which economists ignored[22]... [25]. Pareto's formula was

$$P(u) = (u/m)^{-a} \tag{14}$$

where $P$ is the proportion of people earning more than some level of income u, and m is the minimum income[23].

## 10. The Meaning of Alpha as a Measure of Risk and Turbulence

Alpha is a characteristic exponent restricted to values [0-2] or rather [1-2]—where 0 < alpha ≤ 2—shapes the distribution it belongs to. The smaller alpha, the heavier (fatter) the tails of the (stable density) distribution are. Several outliers (extreme outcomes) will be observed.

As shown, alpha wanders round 2, meaning: a normal distribution since 1750 and till 1975 (225th year). From 1975 and till 2015, however, alpha gradually fell from 2 to 1.4561976 = 1.46 (rounded) for n = 10 on 266 yearly observations. As argued by Peters [8] turbulence[24] is related to the velocity of a fluid and not to fluid's movement, entailing 0 ≤ H < 0.50. As alpha decreases, both the occurrence rate and the strength of outliers increase, resulting to very impulsive processes. In **Figure 15** the alpha coefficient of the "shipping index of dry cargo"

[22]Output rises faster than the amount by which all factors used increased. The total value (and quantity) of production increases, and total profits, as the amount of sales increases entailing higher ability for better quality and marketing. Best example: the car manufacturing in Japan. Learning by doing is also involved. These scale economies implies also lower cost as production increases. Though economists have excluded time from price determination, economies of scale exist also when production gets faster, as scale increases, as this happened with building the ships for "Liberty" during 2nd World War; the last ship of some 2,800 ships was constructed in about 2 days…cost is also a function of time as cost runs, and revenue is a function of time too!

[23]Let the minimum income be m = $10,712 per year; what % of people earns 10 times that (?) *i.e.* $u$ = $107,120? We divide this by $m$, = 10 = $u/m$. Then we calculate $(u/m)^{-a} = (u/m)^{-3/2}$ {2} = 3.2%. Greeks are ~6 million people (active) and the percentage of people earning €90,120 per year or more, are 192,000 (assuming the target -by the Government—of a monthly minimum wage of €751 per month).

[24]The turbulence of a market is in the velocity of its price changes, and not in the changes themselves.

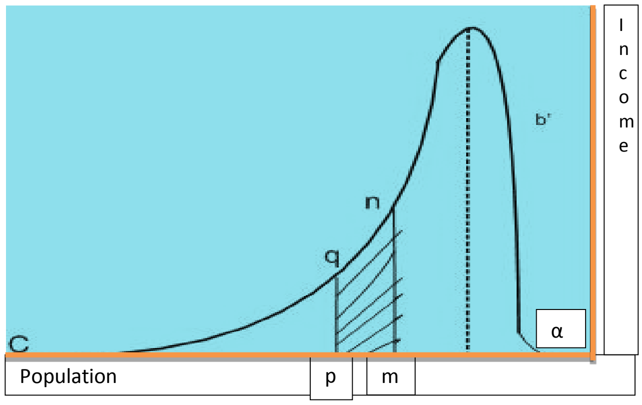



**Figure 14.** Pareto's income curve, 1909, of wealth/income distribution. Source: Pareto's income curve 1909, redesigned from Mandelbrot and Hudson [4].

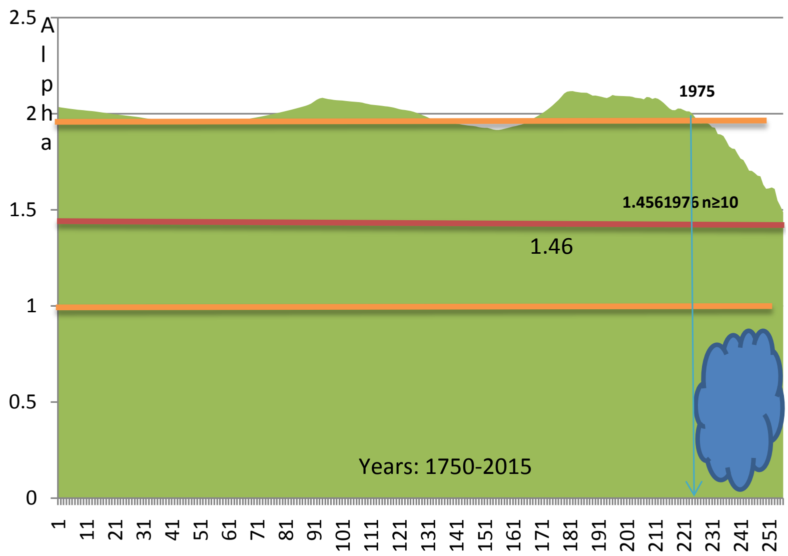



**Figure 15.** The alpha exponent in the index of dry cargo freight rates, 1741-2015. Source: Stopford [2] index 1741-2015 as in **Figure 1**, Rescaled range and excel, given 1/H = alpha.

is plotted against time (years) since 1741 and till 2015[25,26].

Financial (and shipping) time series are known to be non-stationary, where the statistical calculations for $\sigma$ etc., are valid only for stationary series. Here we have applied 1st logarithmic differences to obtain stationarity. This transformation is due to Box and Jenkins [26].

The tendency towards catastrophes (turbulences) has been called by Mandelbrot [27] "Noah effect" or the ∞ variance syndrome [8]. Fat tails are caused by crashes and stampedes, which tend to be abrupt and discontinuous. So, turbulence is related to small alphas ≤ 2 and ≥1 and especially ≤1.70. There are 13

[25]One observation is used for the calculation of the 1st logarithmic differences—where time series are made stationary- and 8 observations were missing due to 2nd World War and 9 observations were omitted as the "rescaled range" method requires. This is the method developed by Hurst H E [17] to determine long-memory effects and fractional Brownian motion.

[26]This is the method developed by Hurst H E [17] to determine long-memory effects and fractional Brownian motion.

years that alpha varies from 1.70 to 1.46 and 17 years that alpha is less than 2 (since 1975) as shown in **Figure 15**. The Noah effect depends on the relative size of one event [4].

## 11. The Way to Forecast Shipping Turbulences

$$\text{Equation:}\quad H = \log(c) + \log(R/S_n)/\log\ n \tag{15}$$

will be used, where c is a constant, R is the range, n is a time index and it equals the number of observations, S is the local standard deviation and H is the Hurst exponent. This is based on Hurst's equation

$$\log(R/\sigma) = K\ \log(N/2) \tag{16}$$

$$\text{or}\quad R = \sigma(\mathrm{N}/2)^{\mathrm{K}} \tag{17}$$

where $K = H$. Hurst [17] found $K = 0.73$; we found $H = 0.69$. The $R/S$ or rescaled range statistic is widely used by now for testing whether long-term dependence is present in time series.

It has the advantage to be non-parametric—ignoring the organization of the original data [4], suitable for stock prices. The R/S formula measures whether—over varying periods of time-the amount by which the data vary from maximum to minimum is > or < than what one would expect, if each data point were independent of the last (normality).

The "fractional Brownian motion", as a generalization to processes which grow at different rates

$$t^H \text{ is: } ([X_H(t) - X_H(0)]^2)^{1/2} \text{ with a linear } |t|^H \tag{18}$$

where $0 < H < 1$ is the Hurst exponent. Einstein [18] defined Brownian motion; his model became the main model for random walk in the study of statistics [22]. Einstein discovered that the distance covered by a random particle undergoing random collisions from all sides is directly related to the square root of time:

$$R = kT1/2 \tag{19}$$

where $R$ is the distance covered, $k$ a constant and $T$ the time index or $n$.

This, however, can be generalized to:

$$R/S = k\ T^H \tag{20}$$

where $T$ = the time index or $n$, or $N$. $R/S$ has no dimension; the power value is equal to $H$. There is no matter if periods are separated by many years; and there is no need for time series to have a characteristic scale. Equation (6) has a characteristic of fractal geometry, as it is scaling in accordance with a power law—the power of $H$. As a result a time series may move covering time at the square root of time-this characterized the time series which are random and $H = 1/2 = 0.50$ (normality).

The most interesting case is the one where time series move at $H > 1/2 \le 1$, called black noise, persistent, as well possessing the Joseph and the Noah effects

[22]. These time series—like shipping time series, with $H = 0.69$[27] as mentioned—are faster, and cover more distance than random walk-the system increasing in one period is more likely to keep increasing in the immediately following period. More important is that these time series has the potential of sudden catastrophes (the Noah effect) or of turbulences! This also allows for short term turbulences, say of 7 years down (according to Joseph effect)…

Forecasting turbulences outside the sample

For forecasting turbulences, we will use $1/H$ = alpha for 2016-2035 using NLTSA (2000) computer program due to Syriopoulos and Leontitsis [28] and the forecasting method "kernel density function" (presented briefly in methodology), which has been proved more reliable [29]. The forecast alpha is presented in **Figure 16**.

**Figure 16** indicates the crisis periods where alpha fell below 2 (3 areas of time), with more serious the one after 1985 and 1989. Persistence for 2035 remained at a higher $H = 0.70$, against 0.68, and $n = 277$, after the 20 forecast values entered into the sample. The new alpha is lower and equal to 1.4286 against 1.47, still <1.70. The period of turbulence now transferred from 1975 to 1983 and then to 1989 till 2035. The index forecast to fall in 2016 from 242 units to 136 in 2035 (216 actual in 2015). Changing two parameters: embedding dimension to 8 from 5 and the number of the nearest neighbors from 16 to 20, alpha fell by 0.04. The new forecast values of the index will be from 128 to 121 (1947 = 100).

As a result, the forecasts indicate that turbulences in shipping dry cargo market will continue and will be intensified by and including 2035; we have 18 years still to wait to see reality if still alive…

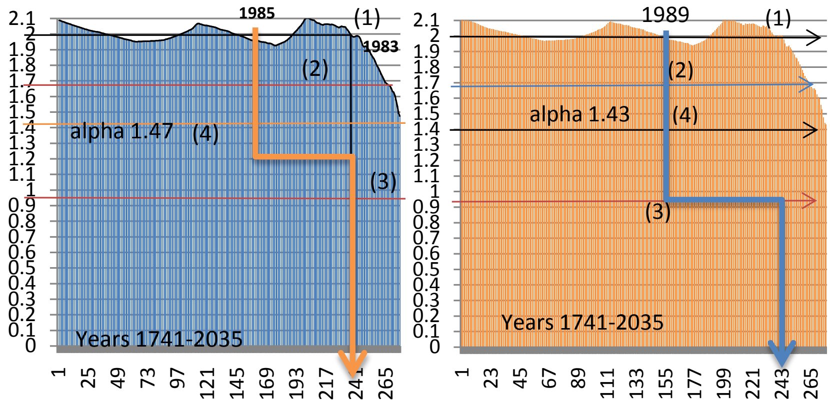
## 12. Conclusions

Turbulence is an extreme economic phenomenon caused by forces, which should have a certain degree of intensity/energy, exhibiting always chaotic behavior. More important, turbulences cannot be captured by a probability density distribution like the Gaussian, because by definition it does not allow for long tails and high peaks—fact indicated by alpha < 2. Alpha < 2 ≥ 1 shows turbulences in the market to which time series belongs to.

The problem of turbulence is one of methodology: markets behave in one of three states: slow, mild and wild. Economists created only one (convenient) method to model all three: "normal distribution". Moreover, the great majority of econometricians do not admit that normal distribution is unable to model "wild" circumstances, with ∞ variance or undefined mean, proposing[28] linear, models like GARCH.

[27]The value $1/H = 1/0.69 = 1.45$ = alpha. The value $2 - H$ gives the fractal dimension of the time series = 1.31. The value $2H + 1$ is the rate of decay of the Fourier series = 2.38.

[28]Studying the history of econometrics we saw, during the transition of the Autoregressive models—AR to ARCH, ARMA, ARIMA, and GARCH, EGARCH and so on, how their authors responded to the defects/critique of their previous models providing new models. GARCH is one of them. Indirectly they have admitted by so doing previous models' limitations/errors. See e.g. ARFIMA models suitable for fractional distributions.




(a) (b)

**Figure 16.** Actual alpha 1741-2015 and forecast alpha 2016-2035. Source: Data from [2] 1741-2015; forecast by "rescale range Method" using NLTSA and "Kernel density estimation"; 1) = normal distribution; 2) = strong variation > 3σ and alpha ≤ 1.70 ≤ 1; 3) alpha = 1, Cauchy distribution; 4) = forecast alpha for 2015-2035 1.47; H = 0.68; (a) embedding dimension 5; time delay 1; the number of nearest neighbors 16; (b) Changing the parameters to embedding dimension 8 and the number of nearest neighbors k = 20, alpha fell to 1.45 from 1.47 and H = 0.70 increased. Then alpha = 1.4286 ~1.43.

GARCH in particular, when volatility jumps, it plugs-in new parameters to make the bell curve grow... and vice versa. The bell distribution is thus treated like a balloon to cope with actual volatility. Moreover, shipping sector and finance are special cases, because their time series—returns, indices or time series—do not follow either Normal distribution or Cauchy distribution…

Very astonishing is the fact that shipping sector since 1741 had time series of dry cargo freight rates, distributed following normal distribution till 1975, as indicated by the prevailing alphas. Turbulences in the sector occurred indeed after 1975: one depression appeared in 1981 till 1987, one in 2009—due to the end-2008 meltdown, and the recent depression—after China's slowdown—in 2011-2018.

Economists indeed accommodated 3 important concepts: "volatility, uncertainty and risk" into one, *i.e.* the $\sigma$ of the bell curve, without reference to the distribution it belongs to. For Cauchy distribution—even if we wanted to define $\sigma$—we cannot do it… because variance is ∞ or undefined...

In addition, normality is a phenomenon of…the long run, it appears when recessions, depressions and turbulences, calm/boil down or even disappears from time series! This denies what Keynes wrote in 1936 that 'in the long run, we are all dead'; because in the long run everything in the economy is more peaceful, as shown by normal distribution… At short time-frames prices vary wildly, and at longer time frames they settle down.

Despite the above, the yearly observations we used for shipping, detected wilderness in the last 13 years (2003-2015) pushing alpha from 2 in the interval [1.70, 1.43]. Shipping companies (and maritime economists) thus may be misled about reality according to the time-frame of data they look at… Minute by minute, hour by hour, day by day, week by week are time-frames that reveal the true wild face of markets; it is then also that decisions are taken… long runs are suitable for plans, but days are only suitable for decisions. Decisions transformed in actions are the blood and the energy for life in the economic organisms like markets. It is this energy that causes turbulences according to its energy, power and intensity.

## References

[1] Brooks, C. (2014) Introductory Econometrics for Finance. 3rd Edition, Cambridge University Press, Cambridge.

[2] Stopford, M. (2009) Maritime Economics. 3rd Edition, Routledge, London. https://doi.org/10.4324/9780203891742

[3] Jiang, S. (2015) More Evidence against the Random Walk Hypothesis. World Scientific, Singapore. https://doi.org/10.1142/9412

[4] Mandelbrot, B. and Hudson, L.R. (2006) The (Mis) Behavior of Markets: A Fractal View of Financial Turbulence. Basic Books, New York.

[5] Ruelle, D. and Takens, F. (1971) On the Nature of Turbulence. *Communications on Mathematical Physics*, **20**, 167-192. https://doi.org/10.1007/BF01646553

[6] Feynman, R. (2006) Turbulence Theory Gets a Bit Choppy. USA Today, Sept. 10. http://www.usatoday.com/tech/science/colmnist/vergano/2006-09-10-turbulence_x.htm

[7] Mello, L. (2008) Fat-Tailed Distributions and Levy Processes.

[8] Peters, E.E. (1994) Fractal Market Analysis: Applying Chaos Theory to Investment & Economics. Wiley, Hoboken.

[9] Anonymous (No Date) Chapter 3, Alpha-Stable Random Variables and Processes. 26-37.

[10] Trevethan, M. and Chanson, H. (2010) Turbulence and Turbulent Flux Events in a Small Estuary. *Environmental Fluid Mechanics*, **10**, 345-368. https://doi.org/10.1007/s10652-009-9134-7

[11] Juarez, F. (2011) Applying the Theory of Chaos and Complex Model of Health to Establish Relations among Financial Indicators. *Procedia Computer Science*, **3**, 982-986.

[12] Lorenz, E. (1963) Deterministic Nonperiodic Flow. *Journal of Atmospheric Sciences*, **20**, 130-148. https://doi.org/10.1175/1520-0469(1963)020<0130:DNF>2.0.CO;2

[13] Mpountis, T. (2004) The Wonderful World of Fractals: A Tour in the New Science of Chaos and Complexity. Leader Books Publications. (In Greek)

[14] Zou, Y., He, K. and Jiang, M. (2015) A Curvelet Based Approach to Time Series Forecasting. *Procedia Computer Science*, **55**, 1325-1330.

[15] Jing, L., Marlow, P. and Hui, W. (2008) An Analysis of Freight Rate Volatility in Dry Bulk Shipping Markets. *Maritime Policy & Management*, **35**, 237-251. https://doi.org/10.1080/03088830802079987

[16] Koopmans, T.C. (1939) Tanker Freight Rates and Tankship Building: An Analysis of Cyclical Fluctuations. De Erven F. Bohn N.V., Haarlem.

[17] Hurst, H.E. (1951) Long-Term Storage Capacity of Reservoirs. *Transactions of the American Society of Civil Engineers*, **116**, 770-799, 800-808.

[18] Einstein, A. (1905) Reference to the Required Movement of Small Particles Moving

inside Stagnant Liquid in Accordance with the Molecule-Kinetic Theory of Heat—A New Determination. Annals of Physics, No 322.

[19] Goulielmos, A.M. and Psifia, M.-E. (2009) Forecasting Weekly Freight Rates for One Year TC 65,000 dwt Bulk Carrier, 1989-2008, Using Nonlinear Methods. *Maritime Policy & Management*, **36**, 411-436. https://doi.org/10.1080/03088830903187150

[20] Goulielmos, A.M. and Psifia, M.-E. (2011) Forecasting Short-Term Freight Rate Cycles: Do We Have a More Appropriate Method than Normal Distribution? *Maritime Policy & Management*, **38**, 645-672. https://doi.org/10.1080/03088839.2011.556673

[21] Sugihara, G. and May, R. (1990) Nonlinear Forecasting as a Way of Distinguishing Chaos from Measurement Error in Time Series. *Nature*, **344**, 734-740. https://doi.org/10.1038/344734a0

[22] Steeb, W.-H. (2008) The Nonlinear Workbook. 4th Edition, World Scientific, Singapore. https://doi.org/10.1142/6883

[23] Schwert, G.W. (2017). http://schert.simon.rochester.edu/volatility.htmdown/ed

[24] Schroeder, M. (1991) Fractals, Chaos, Power Laws: Minutes from an Infinite Paradise. Dover Publications, Mineola.

[25] Arthur, W.B. (1994) Increasing Returns and Path Dependence in the Economy. The University of Michigan Press, Ann Arbor. https://doi.org/10.3998/mpub.10029

[26] Box, G.E.P. and Jenkins, G.M. (1976) Time Series Analysis: Forecasting and Control. S.F., Holden Day.

[27] Mandelbrot, B. (1972) Statistical Methodology for Non-Periodic Cycles: From the Covariance to R/S Analysis. *Annals of Economic and Social Measurement*, **1**, 259-290.

[28] Syriopoulos, C. and Leontitsis, A. (2000) Nonlinear Time Series Analysis with NLTSA V.2 Computer Package. Anikoula Publications, Thessalonica. (In Greek)

[29] Goulielmos, A.M. (2017) The Myths about Forecasting, Business Cycles and Time Series: With an Application to Shipping Industry. *Modern Economy*, **8**, 1455-1477. https://doi.org/10.4236/me.2017.812097