Econophysical bourse volatility – Global Evidence

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Abstract: Financial Reynolds number (Re) has been proven to have the capacity to predict volatility, herd behaviour and nascent bubble in any stock market (bourse) across the geographical boundaries. This study examines forty two bourses (representing same number of countries) for the evidence of the same. This study finds specific clusters of stock markets based on embedded volatility, herd behaviour and nascent bubble. Overall the volatility distribution has been found to be Gaussian in nature. Information asymmetry hinted towards a well-discussed parameter of 'financial literacy' as well. More than eighty percent of indices under consideration showed traces of mild herd as well as bubble. The same indices were all found to be predictable, despite being stochastic time series. In the end, financial Reynolds number (Re) has been proved to be universal in nature, as far as volatility, herd behaviour and nascent bubble are concerned.

Keywords: Financial Reynolds number, volatility, Herding, Bubble, Econophysics

JEL Classification Code: G170, G410, A120

Introduction

Central banks often check bourse volatility, though without having direct connection with it. More often than not bourse volatility has been found to indicate the financial health of an economy. Thus it becomes essential to track it on a regular basis. Value at risk, mean variance, mean deviation and standard deviation are all being sharing a common premise of Gaussian distribution share the similar shortcoming as well. The never-ending threat of an undetected Fat-tail in a risk-return distribution makes the work really difficult in extreme scenarios (read during 'Black Swan' event). Hence a research gap was profound and largely existing for a long period. Economic theories are essentially micro-theories which work precisely for given conditionality quite unlike theories from 'Physical Science'. A uniform theory having a cobbled approach between these two diverging disciplines holds the key. Noted Economist and Noble-Lauriat Samuelson himself had worked on Bachelier's work and introduced GBM (Geometric Brownian Motion) to showcase the continuity of the trajectory of an stock warrant price [25,26]. Samuelson despite being an economist kept the cornerstone for the econophysics research in future. The fundamental hypothesis of econophysics and financial economics remained the same. It's nothing but 'stationary ergodic hypotheses'. In simple terms it can be described as a fact that 'past data would be able to determine future data'. He did point out this fundamental attribute of econophysics quite extensively though [26].

The enchanting story of econophysics is furthered in the literature review section in detail. Coming back to the premise of this very study we find construction and validation of an apt econophysics proxy. Financial Reynolds number has been constructed to find the volatility of stock markets [12]. It originated from theories of fluid mechanics and found itself aptly nestled into the domain of quantitative finance. Some studies of eminence found stock/index movement in a bounded space (with the circuit filters on and time being limited) quite similar to fluid movements in a finite Hilbert space [16,28]. However, provided an opportunity both index as well as the fluid tend to explode. The expression of explosion has been coined as 'financial Reynolds number (Re)', where the numerator is representing market momentum and the denominator is representing market viscosity [11,12]. 'Relative Volatility Index (RVI)' remained a tool for most technical analysts to prepare the volatility based prediction root in the short run. Similarly 'Ease of Movement (EMV)' though rationally represents the viscosity of the stock market was used for judging market liquidity condition. A study bridged all the gaps and collated more than seven related and relevant however scattered studies to mathematically construct the much awaited 'volatility proxy'. Since, it got germinated from the trailblazing work of Osborne Reynolds in the area of fluid mechanics, thus it was called 'financial Reynolds number (Re)'. An interesting observation emerged out from this work.

Naturally viscosity tending to zero will bring in an infinite volatility or rather avalanche explosion. Though 'financial Reynolds number (Re)' was primarily constructed to serve as a volatility proxy yet it was found to indicate some more critical parameters as well. It can successfully indicate embedded herding and traces of nascent bubble as well [11]. However economic proxy and econophysics proxy have a fundamental difference. A valid econophysics proxy ideally works more like a uniform theory unlike economic micro-theories. It should ideally work across the geographical, political and economic territories. The econophysical proxy ideally should be tested globally at an empirical level to provide necessary inputs for the confirmation of the very fact that it's a true proxy that could well represent volatility irrespective of the country, currency or any other external parameter. The previous works suggested that all these necessary indicators are working in the Indian context (both regular and also in High Frequency Trading). This study is an attempt to validate the proxy and its allied functionalities across various bourses (42 stock markets to be precise) over different period of time (to take care of their random nature).

Hence this study has three clear objectives:

1. To check the predictability aspect of 'Financial Reynolds number (Re)' for 42 stock exchanges globally
2. To check the bubble and herding possibilities for all the 42 stock markets
3. To check the presence of information level while all these things happen for all the 42 stock markets

Thus specific tools are put into use to construct and validate such a huge investigation:

1. 'Financial Reynolds number' equation provided in the maiden work on the same to calculate the same for all the stock exchanges under investigation
2. Bubble, herding possibilities are checked using 'Hurst Exponent' and 'Fractal Dimension' on the empirical time series of financial Reynolds number (Re) of all 42 stock markets
3. Information asymmetry has been put into test by 'Shannon's Entropy' for all 42 stock markets

Often it has been claimed that the global economy is coupled. All economies are interlinked and form a complex network system. That network system is pretty brittle in nature as per May-Wigner theorem [27], even practically as well due to the superior speed and quality of information transfer across the globe. This study will confirm or validate that theory as well. Though all the stock markets aren't sharing the same length of time, yet majority of their time has been together. These kind of observations could be generated from those *majority time period*.

Literature Review

This quest started along the lines of an Indian-Bosnian study. Which unearthed the new volatility proxy, namely the 'financial Reynolds number (Re)'; we have to travel back in time by about a century or so to set a premise. Bachelier's trailblazing study on La Boursa was based on cotton prices [17], which laid the foundation of many a discipline in the future. Even award-winning Black-Scholes-Miller model was a variant of his model only [15]. Two American researchers furthered the work of Bachelier in true sense, while showcasing the scaling behaviour of power law matches that of financial markets [22]. The Asymptotic decay in the Fat tail distribution in stock markets were showcased in coming years [1,14,24]. All these seminal works indicated a true potential for a future econophysical volatility proxy. Another path-breaking work came from the 'father of Fractals', Benoit Mandelbrot, which showed physical turbulence and financial turbulence are very similar [21]. An American scientist used the fluid mechanics concept of 'Reynolds number for the very first time' and he showcased the model and mathematical construct for cash flow viscosity-based Reynolds number [20]. Financial Reynolds number was given a completely different construct by two Polish scientists [16]; they calculated the equilibrium of a market from the movement of particles in a rotary system around a central point. While using Caldor's cobweb model on the Warsaw stock exchange they finally concluded that equilibrium is found only in the short run. Orthogonal projection of rotary trajectory was used in investigating stock price explosive threshold was unique and trailblazing by all means.

Series of studies came to decipher the true picture behind bubbles and crashes in financial markets. These studies sometimes used drawdown, log-periodic power law, complex networks or herding behaviour indices alongside fear index as well [7,18,30]. A Chinese research group showed a very interesting resemblance between an active stock index with atoms moving inside a finite Hilbert space [29]. However, they didn't continue further on the same trail. Another researcher of repute conducted his rate of return construction inside similar looking finite Hilbert space [6]. These added the required fuel for a serious work on finding volatility inside a finite Hilbert space. Stock exchanges while in operation looks very similar to finite Hilbert space. Where the index can go to finite directions (prices and volume of the index), upto finite limits (till the upper as well as the lower circuit filters) and till finite time (operating time of the stock market under consideration). Another direction was added by a Portuguese research group by introducing information entropy or Claude Shannon's Entropy in action [5]. Higher the entropy, lower the information thus higher the uncertainty prevailing in the markets. However, entropy for more than one reason becomes uni-dimensional in nature. An ensembleing of all these works were required with a predictable mathematical construct under a fundamentally sound rational premise. The Indian-Bosnian study provided exactly the same. They used the concept of Osborne Reynolds directly, while linking it to two well-known financial tools in a cobbled manner. 'Relative Volatility Index (RVI)' represented 'market momentum' and 'Ease of Movement (EMV)' represented 'market viscosity' by all means [3,8]. Thus 'financial Reynolds number (Re)' was introduced. The same research group has also tested the same proxy to find out its own predictability quotient as well as Herd Behaviour along with profound traces of fractal footprint successfully for Indian stock markets [11,13]. However, as mentioned earlier an econophysical proxy is only valid if tested positive empirically over a large sample and in a random manner. This study is a humble attempt to answer the same question.

Methodology

This work has been woven using a cobbled methodology, which puts four methods sequentially to test the 'explosive threshold', 'Herd behaviour', and 'nascent bubble formation' and 'information uncertainty indication' for all the stock exchanges under investigation. Central Banks, Qualified Institutional Buyers and Foreign Institutional Investors can all use these outcomes for their tracking and decision making purpose.

Country specific stock exchange data was used for calculation of financial Reynolds number (Re). Each stock exchange data (day's high, day's low, day's close, day's opening apart from volume traded) has been captured and financial Reynolds number (Re) has been calculated (following equation 1). The time period of data set is from August 2011 to August 2018. Each country has approximately 1700 data points for the calculation. Total data set under consideration is 71,400.

Financial Reynolds number

Conceptually, Financial Reynolds number (Re)= Stock Market Momentum/ Stock Market Viscosity [12]. Hence, if viscosity in a stock market being higher (provided the momentum remain constant), the 'Re' will come down; on the other hand, in an hypothetical situation of stock exchange viscosity tending to zero, 'Re' will rush towards ∞ (infinity) in no time. Viscosity has been represented in this case using 'Ease of Movement' constructed by Richard Arms. It's an amalgamation of Dorsey's 'Relative Volatility Index(RVI)' in numerator and Arms's 'Ease of Movement(EMV)'in denominator [3,8].

The equation provided for the same is:

$$Re = (100\,ʊ̈ / (ʊ̈ + \delta)) / (\mathcal{Q}/Ч) \tag{1}$$

Where,

$\mathcal{Q}$= (High+Low)/2 – (Prior High+Prior Low)/2

Ч= (Volume/1, 00,000,000)/(High- Low)

ʊ̈ – Wilder's smoothing of USD

USD = If close > close (1) then SD, S else 0; 10 day SD is in use

δ – Wilder's smoothing of DSD

DSD = If close < close (1) then SD, S else 0; 10 day SD is in use

S = Specified period for the standard deviation of the close (should be 10 days according to Dorsey).

N = Specified selected smoothing period (should be 14 days according to Dorsey).

Generalized Hurst Exponent and Fractal Dimension

This is an asymptotic behavioral pattern of a rescaled time series.

$$E\left[\frac{R(n)}{S(n)}\right] = Cn^{H} \tag{2}$$

where R(n) is the range of the values, S(n) is their standard deviation, $E\left[\frac{R(n)}{S(n)}\right]$ is the expected value, n is the number of data points in the specified time series, C is a constant, H is the Hurst exponent Relation of Hurst exponent with fractal dimension can be defined as :

$$D= 2 - H \tag{3}$$

Table 1.0: This table showcase various zones of Hurst Exponent and their interpretation

Hurst Exponent	Interpretation
H < 0.5	Non-persistent, no pattern, no herding
H = 0.5	Random walk, completely stochastic
H > 0.5	Persistent, clear pattern, trace of herding

Fractal Dimension

Monofractal dimension has been used in this study. Fractal is a geometric shape that determines the smoothness of any surface (read as volatility surface). Suppose if, Hurst exponent is 1 (highest predictability possible), then fractal dimension also becomes 1 (called as smooth surface). On the contrary if Hurst exponent is 0.3 then fractal dimension will be 1.7 (quite rough indeed). Hence, rougher surfaces indicate less-predictability for a self-similar (ergodicity) stochastic process.

Shannon Entropy (Information Theory)

For a given probability distribution Pi = P (xi), where i = 1, 2, 3, 4….n, where is a given random variable. The formula is:

$$S(x_i)=-\sum_{i=1}^{n} P_i \log(P_i) \tag{4}$$

Shannon's entropy is proved to be quite successful in the treatment of equilibrium oriented systems (such as stock markets or similar stochastic time-series) in which the random series will have the same average behaviour over time as well as space (that is called "ergodicity"). Conceptually speaking the higher the Shannon Entropy, the lower the information availability in the market, hence the higher is the uncertainty.

Assumptions that are taken in this study:

1. Both financial Reynolds number (Re), Shannon entropy share the same upper limit of tolerance, i.e. '3' (this has been considered purely from empirical observation)
2. Monofractal Dimensions have been under consideration instead of complex multifractal dimension
3. Stationarity, Gaussian distribution (of volatility distribution) and ergodicity (as a premise for Econophysics) have been considered
4. Marginally different time period for all the bourses have been considered (more than 80% were overlapping though), to introduce randomness in calculation

Outcome

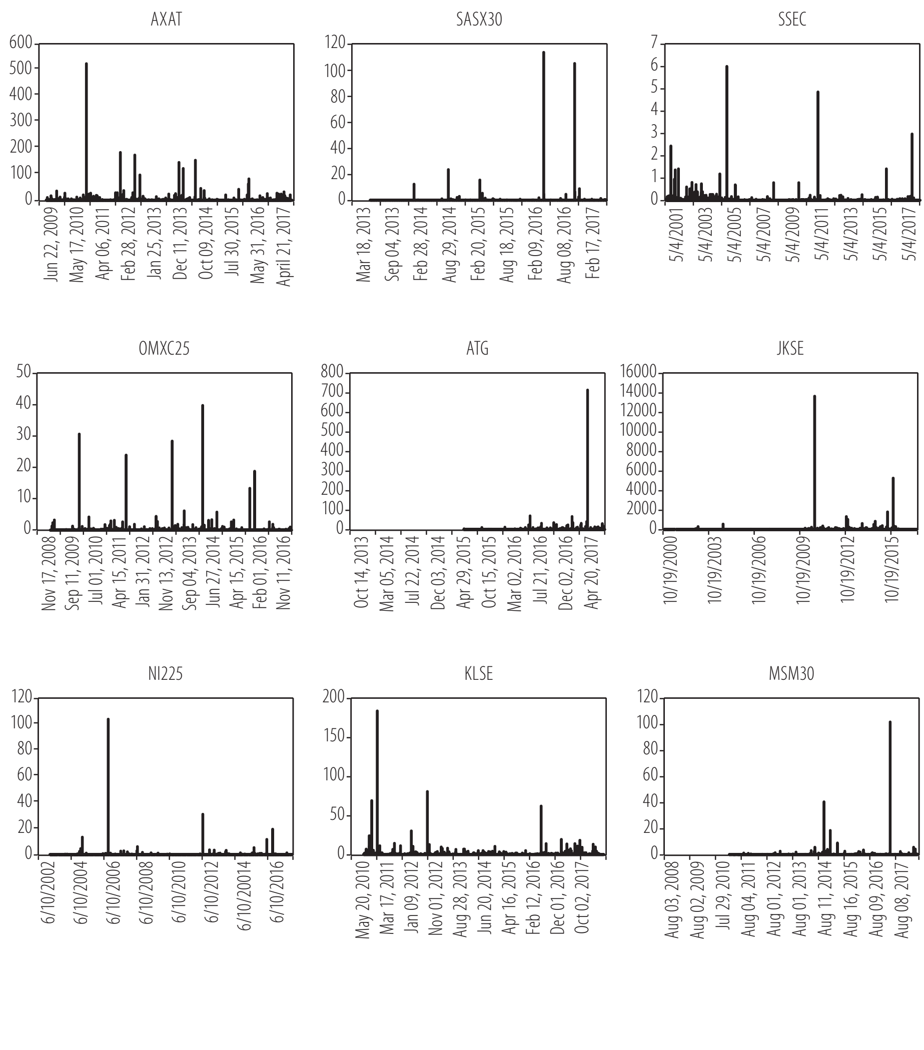
Table 1.1: This table depicts the highest/lowest values of Re, Hurst Exponents, Fractal Dimensions (FD) and Shannon Entropy (SE) for forty-two stock exchanges globally

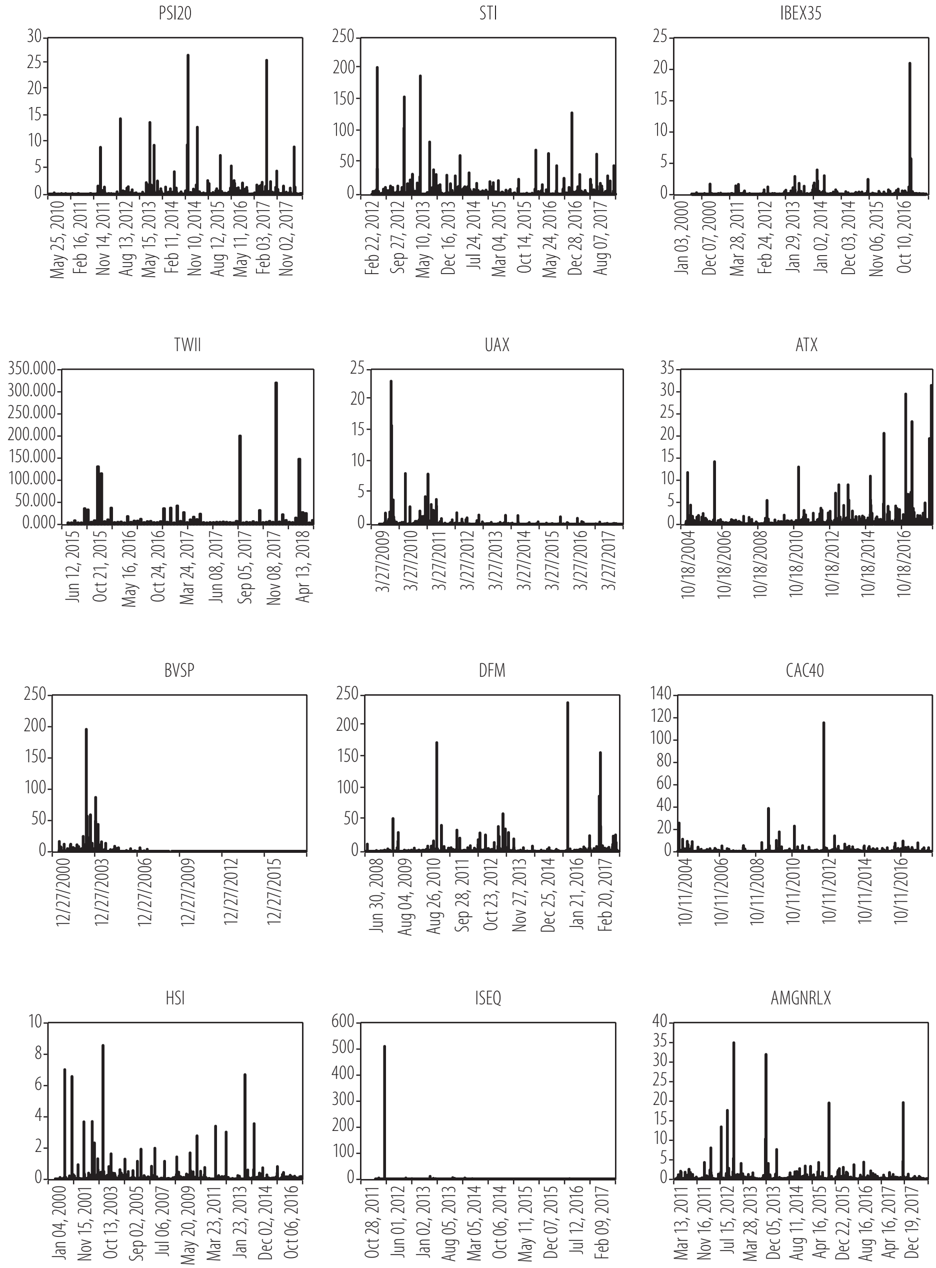
Index	Re (High)	Re (Low)	Hurst	FD	SE
AXAT	532.63	0	0.46	1.54	3.31
ATX	31.16	0	0.59	1.41	2.98
BEL 20	105.54	0	0.6	1.4	2.69
SASX30	113.61	0	0.55	1.45	2.55
BVSP	190.99	0	0.56	1.44	2.42
GSPTSE	28.12	0	0.58	1.42	2.75
SSEC	5.9	0	0.57	1.43	2.23
EGX100	3671	0.02	0.52	1.48	3.44
OMX H25	41.64	0	0.54	1.46	3.45
CAC 40- FCHI	121.95	0	0.59	1.41	3
DAX30	77.31	0	0.58	1.42	2.76
ATG	725.93	0	0.55	1.45	3.32
Hang Seng	823.94	0	0.59	1.41	2.83
NIFTY 50	94.89	0	0.5	1.5	2.94
JKSE	13873	0	0.6	1.4	3.36
ISEQ	520.27	0	0.6	1.4	2.86
FTSE MIB	58.28	0	0.54	1.46	2.64
NI225	107.86	0	0.6	1.4	2.73
AMGNRLX	34.54	0	0.51	1.49	3.02
BLSI	194.88	0	0.56	1.44	2.75
KLSE	184.81	0	0.55	1.45	3.21
BMV IPC	66.31	0	0.56	1.44	2.8
AEX	612.92	0	0.6	1.4	3.13
MSI	102.74	0	0.62	1.38	2.71
PSEI	44.43	0	0.59	1.41	2.97
WIG20	49.2	0	0.6	1.4	2.92
PSI 20	26.91	0	0.64	1.36	2.88
BET	99.13	0	0.53	1.47	2.97
TASI	48.68	0	0.59	1.41	2.98
STI	202.36	0	0.53	1.47	3.36
JSE T40	14.92	0	0.6	1.4	2.67
KOSPI	58.81	0	0.61	1.39	2.27
IBEX 35	21.89	0	0.6	1.4	2.67
CSE	80.43	0	0.61	1.39	2.85

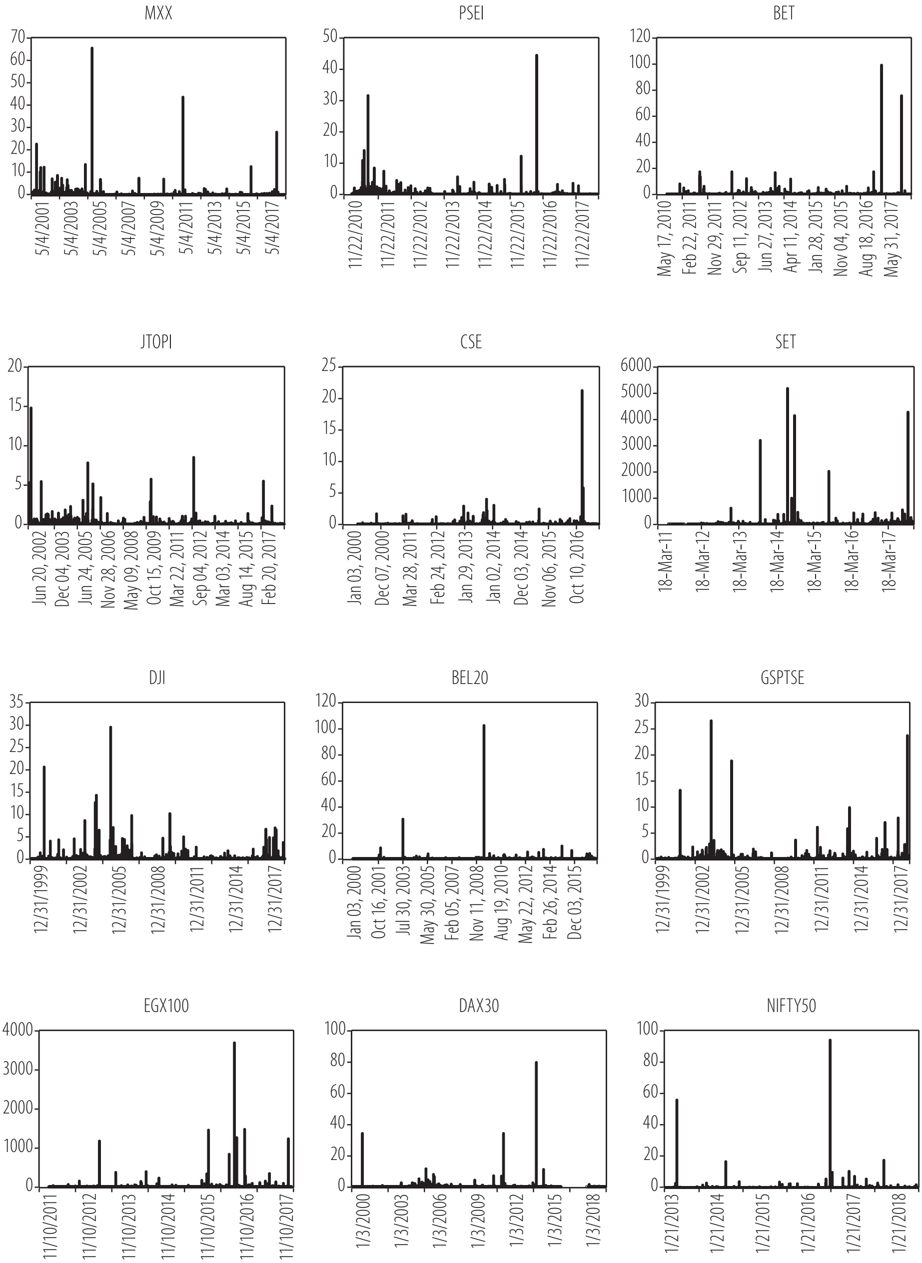
OMX S30	5434	0.01	0.58	1.42	3.57
TWII	315.34	0	0.56	1.44	2.68
SET	5130	0	0.62	1.38	3.44
BIST100	9.06	0	0.52	1.48	2.54
DJI	29.4	0	0.57	1.43	2.75
UAX	23.7	0	0.53	1.47	3.1
DFM	233.62	0	0.58	1.42	3.21
VN	121.66	0	0.6	1.4	2.64

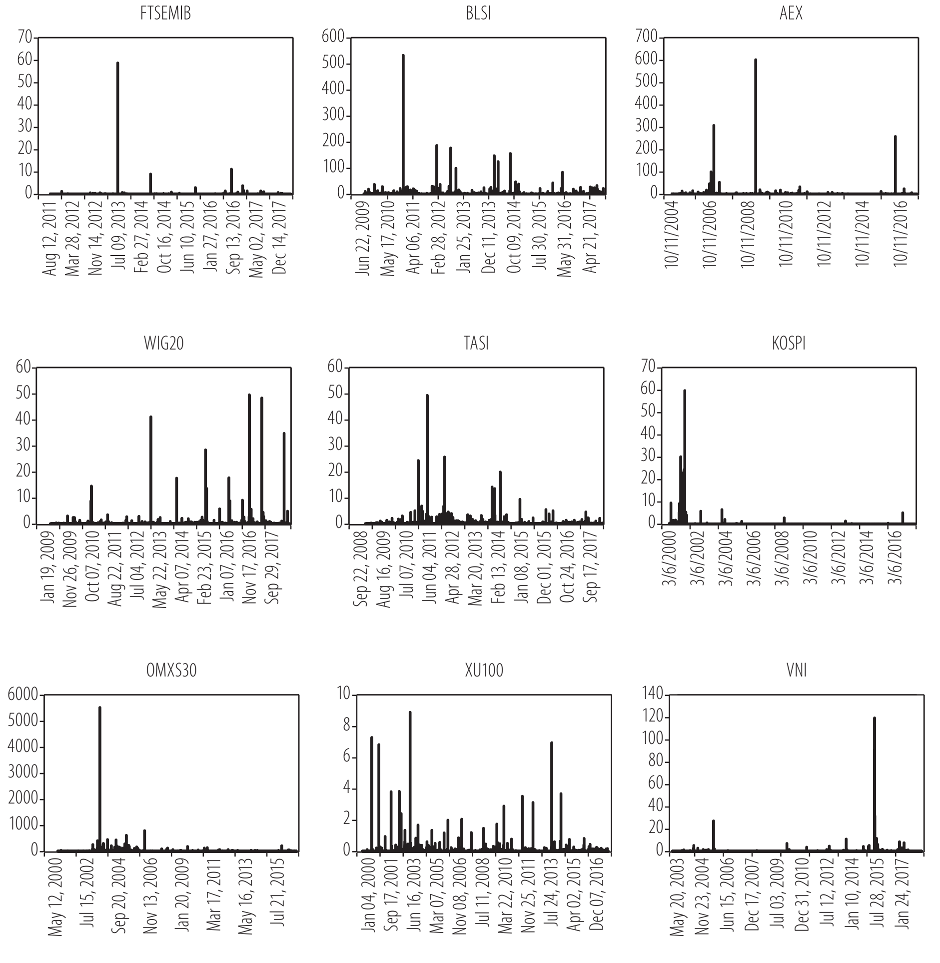
Source: Calculated by the first author

Graph 1.0: These graphs depict the actual fluctuations of 'financial Reynolds number (Re)' for all the forty-two stock exchanges globally




PSI20
May 25, 2010
Feb 16, 2011
Nov 14, 2011
Aug 13, 2012
May 15, 2013
Feb 11, 2014
Nov 10, 2014
Aug 12, 2015
May 11, 2016
Feb 03, 2017
Nov 02, 2017
STI
Feb 22, 2012
Sep 27, 2012
May 10, 2013
Dec 16, 2013
Jul 24, 2014
Mar 04, 2015
Oct 14, 2015
May 24, 2016
Dec 28, 2016
Aug 07, 2017
IBEX35
Jan 03, 2000
Dec 07, 2000
Mar 28, 2011
Feb 24, 2012
Jan 29, 2013
Jan 02, 2014
Dec 03, 2014
Nov 06, 2015
Oct 10, 2016
TWII
Jun 12, 2015
Oct 21, 2015
May 16, 2016
Oct 24, 2016
Mar 24, 2017
Jun 08, 2017
Sep 05, 2017
Nov 08, 2017
Apr 13, 2018
UAX
3/27/2009
3/27/2010
3/27/2011
3/27/2012
3/27/2013
3/27/2014
3/27/2015
3/27/2016
3/27/2017
ATX
10/18/2004
10/18/2006
10/18/2008
10/18/2010
10/18/2012
10/18/2014
10/18/2016
BVSP
12/27/2000
12/27/2003
12/27/2006
12/27/2009
12/27/2012
12/27/2015
DFM
Jun 30, 2008
Aug 04, 2009
Aug 26, 2010
Sep 28, 2011
Oct 23, 2012
Nov 27, 2013
Dec 25, 2014
Jan 21, 2016
Feb 20, 2017
CAC40
10/11/2004
10/11/2006
10/11/2008
10/11/2010
10/11/2012
10/11/2014
10/11/2016
HSI
Jan 04, 2000
Nov 15, 2001
Oct 13, 2003
Sep 02, 2005
Jul 06, 2007
May 20, 2009
Mar 23, 2011
Jan 23, 2013
Dec 02, 2014
Oct 06, 2016
ISEQ
Oct 28, 2011
Jun 01, 2012
Jan 02, 2013
Aug 05, 2013
Mar 05, 2014
Oct 06, 2014
May 11, 2015
Dec 07, 2015
Jul 12, 2016
Feb 09, 2017
AMGNRLX
Mar 13, 2011
Nov 16, 2011
Jul 15, 2012
Mar 28, 2013
Dec 05, 2013
Aug 11, 2014
Apr 16, 2015
Dec 22, 2015
Aug 16, 2016
Apr 16, 2017
Dec 19, 2017


MXX
5/4/2001 5/4/2003 5/4/2005 5/4/2007 5/4/2009 5/4/2011 5/4/2013 5/4/2015 5/4/2017
PSEI
11/22/2010 11/22/2011 11/22/2012 11/22/2013 11/22/2014 11/22/2015 11/22/2016 11/22/2017
BET
May 17, 2010 Feb 22, 2011 Nov 29, 2011 Sep 11, 2012 Jun 27, 2013 Apr 11, 2014 Jan 28, 2015 Nov 04, 2015 Aug 18, 2016 May 31, 2017
JTOPI
Jun 20, 2002 Dec 04, 2003 Jun 24, 2005 Nov 28, 2006 May 09, 2008 Oct 15, 2009 Mar 22, 2011 Sep 04, 2012 Mar 03, 2014 Aug 14, 2015 Feb 20, 2017
CSE
Jan 03, 2000 Dec 07, 2000 Mar 28, 2011 Feb 24, 2012 Jan 29, 2013 Jan 02, 2014 Dec 03, 2014 Nov 06, 2015 Oct 10, 2016
SET
18-Mar-11 18-Mar-12 18-Mar-13 18-Mar-14 18-Mar-15 18-Mar-16 18-Mar-17
DJI
12/31/1999 12/31/2002 12/31/2005 12/31/2008 12/31/2011 12/31/2014 12/31/2017
BEL20
Jan 03, 2000 Oct 16, 2001 Jul 30, 2003 May 30, 2005 Feb 05, 2007 Nov 11, 2008 Aug 19, 2010 May 22, 2012 Feb 26, 2014 Dec 03, 2015
GSPTSE
12/31/1999 12/31/2002 12/31/2005 12/31/2008 12/31/2011 12/31/2014 12/31/2017
EGX100
11/10/2011 11/10/2012 11/10/2013 11/10/2014 11/10/2015 11/10/2016 11/10/2017
DAX30
1/3/2000 1/3/2003 1/3/2006 1/3/2009 1/3/2012 1/3/2015 1/3/2018
NIFTY50
1/21/2013 1/21/2014 1/21/2015 1/21/2016 1/21/2017 1/21/2018



Source: Calculated by the first author

Table 1.2: This table provides a plausible explanation of (Table 1.1) from the point of views of Herding/Bubble/Predictability (derived from Hurst Exponent and Fractal Dimensions) and Information (derived from Shannon Entropy)

Countries	Herding	Bubble	Predictability	Information
Portugal	Mild	Mild	High	More
Thailand	Mild	Mild	High	Less
Oman	Mild	Mild	High	More
Sri Lanka	Mild	Mild	High	More
South Korea	Mild	Mild	High	More
Belgium	Mild	Mild	High	More

Spain	Mild	Mild	High	More
Ireland	Mild	Mild	High	More
Indonesia	Mild	Mild	Moderate	Less
Vietnam	Mild	Mild	Moderate	More
Poland	Mild	Mild	Moderate	More
Netherlands	Mild	Mild	Moderate	Less
Japan	Mild	Mild	Moderate	More
South Africa	Mild	Mild	Moderate	More
Saudi Arabia	Mild	Mild	Moderate	More
France	Mild	Mild	Moderate	More
Austria	Mild	Mild	Moderate	More
Philippines	Mild	Mild	Moderate	More
Hong Kong	Mild	Mild	Moderate	More
UAE	Mild	Mild	Moderate	Less
Canada	Mild	Mild	Moderate	More
Sweden	Mild	Mild	Moderate	Less
Germany	Mild	Mild	Moderate	More
USA	Mild	Mild	Moderate	More
China	Mild	Mild	Moderate	More
Mexico	Mild	Mild	Moderate	More
Brazil	Mild	Mild	Moderate	More
Taiwan	Mild	Mild	Moderate	More
Lebanon	Mild	Mild	Moderate	More
Malaysia	Mild	Mild	Moderate	More
Greece	Mild	Mild	Moderate	Less
Bosnia	Mild	Mild	Moderate	More
Finland	Mild	Mild	Moderate	Less
Italy	Mild	Mild	Moderate	More
Romania	None	None	Relatively Low	More
Ukraine	None	None	Relatively Low	Less
Singapore	None	None	Relatively Low	Less
Egypt	None	None	Relatively Low	Less
Turkey	None	None	Relatively Low	More
Jordan	None	None	Relatively Low	Less
India	None	None	Relatively Low	More
Australia	None	None	None	Less

Source: Calculated by the first author

Interpretation

This entire empirical investigation can be broken down to three clusters with different degrees of predictability, presence of nascent traces of bubble and Herd behaviour. Moreover, rather than being lost in the linguistic 'jargon-filled' interpretation this study focuses towards the presentation of the plausible and simplified outcome. Thus the readers can use it as a decision benchmark for their rather difficult decision making process. However, the technical interpretations are provided as well to quench the thirst of the true researchers.

The first cluster has been found with high predictability, mild bubble and herding traces:

Technically this means clear and persistent pattern amidst a stochastic time series representing bourse volatility (read as 'financial Reynolds number'). Despite higher predictability the embedded herd as well as budding nascent bubble traces are relatively lower. This cluster has been found to be truly self-similar stochastic series. Surface roughness lowers (fractal dimension is 1.4 with Hurst above 0.6) for a self-similar process paving the way forward for fruitful prediction. Despite such a long length of time under consideration (more than 20 years for each country) some countries still clock Hurst exponent above 0.6. This indicates, those countries in the shorter format may've faced crisis in between and the average of Hurst exponent being higher confirms the length of that crisis to be fairly long enough. Two studies have proved empirically that Hurst increases during economic/ financial crisis amidst profound fractal footprint [13,23].

More plausible explanation has been provided for the first cluster:

Countries namely Portugal, Thailand, Oman, Sri Lanka, South Korea, Belgium, Spain and Ireland constitute the first cluster. Interestingly, three countries of PIIGS economy are present here (Portugal, Ireland and Spain). One more interesting fact from this cluster has been 'Thailand' as a stock market. Thailand has spotted higher Shannon Entropy with 3.44 hence lesser the information thus more uncertainty is prevailing. Hence, four countries come clean on all the aspects. It could be noted that Oman, Sri Lanka, South Korea and Belgium though have mild traces of herding and bubble yet shows potential as predictability in these markets are accurate. It could well be due to the fact that they attract lesser FII and QIB funds and consist of more 'sticky money' or in other words domestic funds. These four countries emerge as the next big thing for the investment banks, hence can be referred to as 'KLOB'. The 'KLOB' economies haven't witnessed explosive exponent (upper limit of financial Reynolds number) more than

106. Hence, medium volatility, low volatility explosion and extremely high predictability personify 'KLOB'.

The second cluster has been found with moderate predictability, mild bubble and herding traces:

Technically speaking, they've medium to high persistent predictability with low traces of herd and possible nascent bubble. Lower average Hurst exponent signifies relatively lower volatile or crisis period financially; it can also be due to scattered periods followed by robust recovery in the bourses. Degree of herd as well as budding bubble reduced in this cluster compared to the first one. Seven countries are having stock markets with higher entropy levels. As the Shannon entropy goes up, chaos increases, information decrease and as a result uncertainty heads north. Mostly Western Europe (more so Scandinavia) and extended Asia (adding Middle East) have found with higher chaos and uncertainty as far as market information is concerned.

More plausible explanation has been provided for the second cluster:

A massive twenty six countries (stock markets) are being observed to represent this cluster. Netherlands and their former colony Indonesia, UAE, Finland, Malaysia, Sweden and Greece were those countries which have lesser information due to higher entropy thus have more uncertainty. Two representations from MINT economy have been found by Mexico and Indonesia. Three BRICS nations are found to be here, namely Brazil, China and South Africa. This cluster has USA, France and Germany representations as well as far as stock markets are concerned. Between the first and second cluster PIIGS gets covered as Italy and Greece featured in second cluster. These economies are predictable in nature however with a degree of moderation. Taiwan, Malaysia, Hong Kong, Poland and Japan too featured in this category. Plenty of large stock markets by their sheer volume have been covered in this cluster (such as Dow Jones, Nikki, DAX, Hang Seng and Shanghai etc.).

The third cluster has been found with low to no predictability, no bubble and herding traces:

Technically speaking, anti-persistent pattern persists here. Self-similar process hasn't been found. Higher fractal dimension is indicating nothing but roughness, which in turn refers back to less-predictability. Lower Hurst indicates that these economies haven't faced too many financial crises in the twenty years under consideration in comparison to the unprecedented bull rally. Higher level of entropy in majority stock markets (in this cluster) proves both information shared has been on the lesser side (asymmetry) or information percolation and interpretation (financial literacy) has been under the cloud. Countries like Singapore could be an exception though; hence more in depth work is required to decipher the truth behind this observation for some countries.

More plausible explanation has been provided for the third cluster:

Eight countries represent this cluster with low to no predictability and no evident bubble or herd behaviour whatsoever. However 63% of this cluster shows 'less information' or 'higher entropy'. This symbolizes higher uncertainty in the stock markets. Ukraine, Singapore, Egypt, Jordan and Australia could well be a difficult ensemble; however, all of them seem to suffer from excess uncertainty (volatility). Australian stock markets remain the only stock market in this forty two which cannot be predicted at all as it follows a pure Brownian motion with a Hurst Exponent of 0.4575. Barring Singapore and Australian other stock exchanges in this cluster are still developing.

This cluster could well be termed as a cluster of 'low financial literacy', at least for most of it (63%). Barring Singapore, Australia and to a certain extent Ukraine the other countries from cluster three have financial literacy level in a range of 22-27% only[19]. Ukraine is not far behind with just 40% of its adults being financially literate. Hence, this cluster could be dominated by a few large players (big bulls) however having opposite thought process. In this bargain their actions in the stock markets may be neutralising their competitors thus the market is not having any directional predictability as well as secular movements (so, no herding and bubble at all). Again, high financial literacy doesn't guarantee stock market participation. Thus, Australia with a score of 64% and Singapore with a score of 59% do not witness much retail participation; rather they remain FII and QIB dominated instead. Interestingly Australian retail participation is on a 10 year decline mode, currently standing around 36% though [4].

Another very interesting observation shows stock markets with 'less information' and 'more uncertainty' exponentially increases from 13% in the first cluster to 63% in the third one (second remained with 27%). The result seems quite obvious though; as predictability decreases 'fear' increases, thus information asymmetry increases giving a sudden rise to Shannon Entropy. Ironically the cluster distribution fits into a pure Gaussian distribution with equal tails as well (body of the distribution is having 26 out of 42 exchanges i.e. 62%, each tail consists of 8 exchanges i.e. 19% each). Moreover, it has been observed that the most of the stock markets barring one (Australian bourse), are having a Hurst exponent of 0.5. Again, all the forty one economies are in a relatively narrow band of Hurst starting from 0.50-0.62. This implies that the international stock markets are coupled and have formed a network, thanks to the superior information flow at all possible time. Further research is required to find, whether this volatility driven network is brittle or not. Some research have happened one the similar area with stock index return instead of volatility measure.

Conclusion

Herding, bubble, information asymmetry and explosive intent embedded in an index often make the decision making process difficult. Micro-theories of social science research cannot generalize the outcomes either. Decision making gets delayed and segment specific in most cases. This study comes out with three conclusive benchmarks (since it's conducted for forty two indices across the globe encompassing as many countries).

1. Predictability- Most stock markets barring one have been proved to be predictable from volatility standpoint to a definite degree, making decision making relatively conclusive as well as decisive.
2. Herding and Bubble- Approximately 81% of the stock markets under consideration was found to have mild levels of herd and nascent bubble, hence no signs to worry for the long term investors since these datasets are mostly from well above seven years zone.
3. Information and uncertainty- The only worrying signal has been noted in 'Information Asymmetry' scale. Approximately 31% stock exchanges were having less information thus more entropy and uncertainty. However, this clearly doesn't indicate the problem point. It could be either related to information decoding, or, information percolation, or, could well be financial literacy as well. Further research is required on the same.
4. Last but not the least, this study confirms the universality of 'financial Reynolds number' as an apt volatility proxy, which can also be used for herding, bubble and information uncertainty measurement.

Needless to say all the central banks, regulatory authorities, QIBs and FIIs will find it easier to conclude the presence and the level of uncertainty, volatility, and herding/bubble post considering this econophysical proxy. Complex systems such as bourses are usually quasi-stable, thus stability (measured by financial Reynolds number) would ensure stable fiscal policy. A recent research echoes the same concept as well [9]. Policy preferences being usually asymmetric stability plays a key role in central bank policies as well as fiscal policies. An Indian work recently paved the way for similar sounding work[2]. Monetary policy too plays a critical role other than just fiscal policy and central bank policy. The infamous global financial crisis of 2008 cardinally challenged traditional monetary policy [10]. This new measurement (financial Reynolds number) will add another dimension to all the policymakers and enable them and apt alternate view.

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References

1. A. Abhyankar, L. S. C. & W. W. (1995). Moment condition failure in high frequency financial data: evidence from the S&P 500. *Applied Economics Letters*, 2(8), 288–290. https://doi.org/DOI: 10.1080/135048595357258
2. Ajaz, T. (2019). Nonlinear Reaction functions: Evidence from India. *Journal of Central Banking Theory and Practice*, 8(1), 111–132. https://doi.org/10.2478/jcbtp-2019-0006
3. Arms, R. W. (1996). *Trading without Fear* (1st ed.). John Wiley and Sons.
4. Australian Securities Exchange. (2013). *Australian Share Ownership Study*. Sydney. Retrieved from https://www.asx.com.au/documents/resources/australian-share-ownership-study-2014.pdf
5. Bentes, S. R., & Menezes, R. (2012). Entropy: A new measure of stock market volatility? *Journal of Physics: Conference Series*, 394(1). https://doi.org/10.1088/1742-6596/394/1/012033
6. Cotfas, L. A. (2013). A quantum mechanical model for the rate of return. *Romanian Reports in Physics*, 65(2), 327-333.
7. Dhaene, J., Dony, J., Forys, M., Linders, D., & Schoutens, W. (2011). FIX - The fear index. Measuring market fear. *FBE Research Report AFI_1155*, (January), 1–17. https://doi.org/10.2139/ssrn.1888335
8. Dorsey, D. (1993). Technical Analysis of Stocks and Commodities, New York.
9. Dumičić, M. (2019). Linkages between Fiscal Policy and Financial (In) Stability. *Journal of Central Banking Theory and Practice*, 8(1), 97–109. https://doi.org/10.2478/jcbtp-2019-0005
10. Fabris, N. (2018). Challenges for modern monetary policy. *Journal of Central Banking Theory and Practice*, 7(2), 5–24. https://doi.org/10.2478/jcbtp-2018-0010
11. Ghosh, B., Krishna, M., Rao, S., Kozarević, E., & Pandey, R. K. (2018). Predictability and herding of bourse volatility: an econophysics analogue. *Investment Management and Financial Innovations, 15*(2), 317–326. https://doi.org/10.21511/imfi.15(2).2018.28
12. Ghosh, B., & Kozarevic, E. (2018). Identifying explosive behavioral trace in the CNX nifty index: A quantum finance approach. *Investment Management and Financial Innovations, 15*(1), 208–223. https://doi.org/10.21511/imfi.15(1).2018.18
13. Ghosh, B. & Kozarević, E. (2019). Multifractal analysis of volatility for detection of herding and bubble: evidence from CNX Nifty HFT. *Investment Management and Financial Innovations*, 16(3), 182-193. doi:10.21511/imfi.16(3).2019.17

14. Gopikrishnan, P., Meyer, M., Amaral, L. A. N., & Stanley, H. E. (1998). Inverse cubic law for the distribution of stock price variations. *European Physical Journal B, 3*(2), 139–140. https://doi.org/10.1007/s100510050292
15. Haug, E., & Taleb, N. N. (2007). Why we have never used the Black-Scholes-Merton option pricing formula. *Social Science Research Network*, (January), 1–11. https://doi.org/10.2139/ssrn.1012075
16. Jakimowicz, A., & Juzwiszyn, J. (2015). Balance in the turbulent world of economy. *Acta Physica Polonica A, 127*(3), A78–A85. https://doi.org/10.12693/APhysPolA.127.A-78
17. L. Bachelier. (1900). Th´eorie de la sp´ eculation. *Ann. Sci. Ecole Norm. Sup, ISSN 0012-9593, 17*, 21–86. Retrieved from http://eudml.org/doc/81146
18. Laloux, L., Potters, M., Cont, R., Aguilar, J. P., & Bouchaud, J. P. (1998). Are financial crashes predictable? *Europhys. Lett., 45*, 1-5.
19. Leora Klapper, Annamaria Lusardi, & Peter van Oudheusden. (2014). Financial Literacy Around the World: Leora Klapper, World Bank Development Research Group Annamaria Lusardi, The George Washington University School of Business Peter van Oudheusden, World Bank Development Research Group INSIGHTS FROM THE STANDARD & POOR'. *The Standard & Poor'S Ratings Services Global Financial Literacy Survey, 10*(04), 509–525. Retrieved from https://www.mhfi.com/corporate-responsibility/global-financial-literacy-survey
20. Los, C. A. (2004). Measuring Financial Cash Flow and Term Structure Dynamics. *SSRN Electronic Journal*.
21. Mandelbrot, B. and R. L. H. (2004). *Misbehavior of markets*. Basic Books.
22. Mantegna, R. N., & Stanley, H. E. (1995). Scaling behaviour in the dynamics of an economic index. *Nature*. https://doi.org/10.1038/376046a0
23. Ormos, M., & Timotity, D. (2016). Market microstructure during financial crisis: Dynamics of informed and heuristic-driven trading. *Finance Research Letters*, 1–15. https://doi.org/10.1016/j.frl.2016.06.003
24. Pan, R. K., & Sinha, S. (2008). Inverse-cubic law of index fluctuation distribution in Indian markets. *Physica A: Statistical Mechanics and Its Applications, 387*(8–9), 2055–2065. https://doi.org/10.1016/j.physa.2007.11.031
25. Samuelson, P. A. (1965). Rational Theory of Warrant Pricing. *Industrial Management Review*, 6(2), 13–39.
26. Samuelson, P. A. (1969). Classical and Neoclassical Theory. In R. W. Clower (Ed.), *Monetary Theory* (pp. 170–190). London: Penguin.
27. Sinha, S., Thess, M and Markose, T. (2013). How Unstable Are Complex Financial Systems? Analyzing an Inter-bank Network of Credit Relations. In *Econophysics of Systemic Risk and Network Dynamics, New Economic Windows* (Vol. 13). Springer Verlag. https://doi.org/10.1007/978-88-470-2553-0_5

28. Zhang, C., & Huang, L. (2010a). A quantum model for the stock market. *Physica A: Statistical Mechanics and Its Applications, 389*(24), 389(24), 5769–5775. https://doi.org/10.1016/j.physa.2010.09.008
29. Zhang, C., & Huang, L. (2010b). A quantum model for the stock market. *Physica A: Statistical Mechanics and Its Applications, 389*(24), 5769–5775. https://doi.org/10.1016/J.PHYSA.2010.09.008
30. Zhang, Q., Sornette, D., BalcIlar, M., Gupta, R., Ozdemir, Z. A., & Yetkiner, H. (2016). LPPLS bubble indicators over two centuries of the S&P 500 index. *Physica A: Statistical Mechanics and Its Applications, 458*. https://doi.org/10.1016/j.physa.2016.03.103