Econophysics Reviews

Preprint · February 2019

DOI: 10.13140/RG.2.2.26695.55206

2 authors:

Bikramaditya Ghosh
Christ University, Bangalore

Krishna Mc
Christ University, Bangalore

Econophysics Reviews

By
First Author: Bikramaditya Ghosh, Assoc. Professor, IMCU, Christ University
bikramaditya.ghosh@christuniversity.in
Second Author: MC Krishna, Assoc. Professor, IMCU, Christ University
krishna.mc@christuniversity.in

Researches in social sciences like Economics and Finance extensively use statistical and mathematical tools. However, it is quite common to assume that the laws of physics and related sciences may not be directly applicable to understanding some of the aspects of Economics and Finance, and predicting the future. However, the researchers of the 21st century in Economics and Finance have established that many a model from Physics can be applied in these areas. Econophysics is proving to be very critical for one's ability to predict some of the common and also not so common phenomena of Financial Markets. A typical hydrodynamic indicator like Reynolds number can be customized to a financial number and can be used to explain the movement of indices and prices of various assets or securities traded in different types of Financial Markets. Some of them have even established through their extensive research that Financial Reynolds number (Re) can be an effective tool for predicting Volatility, herding and also the formation of a bubble in the stock markets. The universality of such findings has been established through studies across bourses of different countries and for different asset classes. The review of literature here tries to trace the findings by different research efforts across the world, which has made a significant contribution in this direction.

Volatility is an enigma that the markets have been chasing from the time man started trading in financial assets. What drives the price discovery and the possible reasons for the volatility of prices has been explained in many a significant work across the globe. In their work(Kempf & Korn, 1999) Kempf & Korn have identified, among other things, that there is a strong non-linear relationship between order size and the price change. This work was carried out on German Index futures data, using the Neural network model. Moving east, Chinese researchers have carried a comparative work between Financial forecasting and 'multi-layer perception by way of back propagation algorithm, with the use of Support Vector Machines (Cao & Tay, 2001).
In one of the work, researchers have used the classical laws of Fluid Mechanics to explain cash flow and its relationship with long-term market dependence(Los, 2004). The relationship between two extreme phenomena viz., Financial Turbulence and Financial Crisis have been explained using mildly reformulated interpretations of Fluid Mechanics in a work on the modern dynamic financial markets (Los, 2004). Exchange rates in the International Financial markets are also subject to rapid price changes, which impact the cross-border trades. The utility of Econophysics in the field of exchange rates has been explained in a work that highlights the multiscaling property of real exchange rates and their relation with exponentially damped Levy Flight (Da Silva, Matsushita, & Gleria, 2003). In another work from the East, it has been clearly established that using some of the primary hypothesis from Quantum mechanics, one can create a quantum model in

Econophysics, wherein one can determine stock price, the wave function of the price movement through a theoretical framework (Zhang & Huang, 2010).

As practitioners and researchers started using different power laws to analyse empirical data to see if a pattern can be identified, a set of researchers tried to provide a view of different questions that are being addressed using the new discipline of econophysics. Researchers state that this effort was primarily due to a desire to accurately describe economic phenomena by carefully analysing the empirical data with models which are based on statistical physics (Sinha & Chakrabarti, 2012). As a continuum to the quantum models suggested by Zhang, researchers from Brazil have stated that Stable Levy process describes the complex issues like turbulence and anomalous diffusion of Financial Markets. They have also asserted that the statistical solutions developed using Econophysics have been able to reason out these phenomena quite convincingly (Paulo & Schinckus, 2013). Financial Analysts and researchers have also used Entropy for asset pricing and portfolio selection. There is a constant comparison of results obtained using Entropy on one side and traditional methods on the other. Such exercises help to sharpen the approach to obtain more accurate results in the pricing of securities and the fluctuation, which is very difficult to predict(R. Zhou, Cai, & Tong, 2013). The advent of Econophysics and related areas of science in the Finance and Economics areas has posed few major theoretical questions. These developments should help evolve the future of finance theories(Jovanovic & Schinckus, 2013). Yet another example to cite here would be that, Chinese researchers have averred that there is a clear correlation between volume and volatility and that both these attributes have more pronounced interaction when the volume and volatility are very high. (Zheng, Qiao, Tenenbaum, Stanley, & Li, 2014). It is none too surprising that they have used Econophysics and Econometrics to come to this conclusion. One more study has used Agent-Based Model method to establish that medium irrationality groups have highest Hurst Exponent and Shanon Entropy for monetary policy, indicating that there would be a high level of volatility which impacts the financial markets and also exhibits herding behaviour (Kim & Kim, 2014). Novel ways of using Lattice Algorithms viz., tilting, trinomial and extrapolation algorithms have been used to improve speed and accuracy to compute tail conditional expectations(Chen & Lu, 2014). Studies also have established that Market nanostructure can utilise String theory to explain the formation of the stable field of information relating to volumes, prices and term structure in the stock markets(Mallik, 2015). Stock price data from the Tehran Stock Exchange was studied for accurate predictability using Artificial Neural Network(Zahedi & Rounaghi, 2015), thereby predicting price variations. New York Stock Exchange data has been studied to establish that algorithmic methods are helpful to identify with a significant level of accuracy, some structural regularities which are normally invisible with the normal statistical tests(Brandouy, Delahaye, & Ma, 2015). The importance of the philosophical attributes of quantum mechanics in explaining market behaviour especially in the pricing of securities and options has also been established(Racorean, 2015). Even image processing techniques have been used to compute the price of financial assets to possibly explain the volatility of asset prices(Daniela Alexandra CRIȘAN, 2015). There exists some perceptible similarity between the rotary trajectories, which are observed in hydrodynamics, and the stock market rotary-spiral trajectory. This has led to the discovery of the econophysics analogue for the stock market, also known as stock market Reynolds number (Re). This effort in a way attempted to address the long-standing question on the reasons for stock market turbulence or volatility(Jakimowicz & Juzwiszyn, 2015).

Price formation and its dynamics have been theorized with the help of quantum mechanics keeping in mind significant similarity between the two. This work has also tried to explain the reason for volatility both in intraday and daily trades (Sarkissian, 2016). Possible explosive moments in the Stock prices and in turn on the indices can be identified and predicted using Reynolds Number. In addition, the possibility of linking this number with the behavioural pattern has been tried using CNX fifty index(Ghosh & Kozarević, 2018). While working on Nifty they found profound traces of bubble and herd in certain spaces of time linked in a queer manner with certain crisis period(Ghosh, M.C., Rao, Kozarević, & Pandey, 2018). This entire work has been conducted based on Hurst exponent, the trusted measure of predictability(Hurst, 1951). Though they have provided enough evidence using various machine learning tools earlier(Ghosh, B., & Srinivasan, 2015; Ghosh, 2017; Ghosh & Srinivasan, 2015), however those remain 'stylized facts' till a robust theoretical model falls in place. Moreover those were all based on either stock returns or absolute values of stock.
However, there have been a few critical reviews of Econophysics as well. It has been stated that models of Econophysics should be taken with caution. They have to be tested for robustness and sound basis for their ability to predict. It is therefore important that some self-organized framework should come out and validate these models which predict financial market behaviour, as it has systemic as well as systematic implications (M. Ausloos, 2013). Econophysics has developed a few research fields viz. Quantum Econophysics and Quantum Artificial Neural Network to build and simulate financial Market models using trading rules. Financial economics and Econophysics approaches the same modelling problems from two distinctly different angles. Where the former focusses on top down and derivation from theoretical premise the later identifies necessary clue from big data crunching and further searching to connect it to an established theory (otherwise it would remain 'stylized facts'). However the twain reaches in the fundamental modeling stage and the key remains in integrating the results (Marcel Ausloos, Jovanovic, & Schinckus, 2016).

The issues of herding behaviour and bubble formation in stock markets have received significant attention from the researchers. We thought it is important to find out some of the key observations and findings on these two aspects, which can aid us in this work.
Stock Markets should ideally work based on the symmetry of Information available to all the participants. However, it is a well-known phenomenon that the market participants tend to follow others for various reasons including their inability to understand how the market actually functions. In one of the research work it has been established that the financial system condensates has a lot of similarity with the Bose-Einstein condensates, where the distribution of investments into speculative securities show similarity with the Pareto distribution, i.e. a vast majority tends to invest in similar assets, showing a semblance of herding behaviour (Staliunas, 2003).
While the stock markets have been offering very attractive gains, the internet era tries to evoke a gambler like a behaviour in the investor. However, such temptations and follow the leader behaviour have created panic across the board not only in isolated markets but globally(Didier Sornette, 2003). One more work suggests that when the investors form a

consistent collective network and show a bearish approach, then such events have led to larger crashes which succeed intermittent positive movements(W. Zhou & Sornette, 2003).

Another study on the Chinese high-frequency data has shown that the investing community tends to show herd behaviour in stock buying with the expectation of high returns. However, they are likely to show disposition effect while selling stocks(Diego, 2010). A study on the group behaviour at the micro and macroeconomic units seems to suggest that groups tend to behave differently at different units. The irrationality varies significantly with different economic units under consideration(Kim & Kim, 2014). Similar to the work by Diego, one more group of researchers have come to the conclusion that herding is generally high in bull markets, where participants are on a buying spree and such a behaviour is milder in bear markets(Gusev et al., 2015). Two classes of herd behaviour indices have been recommended to measure the market perception relating to the extent of relation that prevails between the random variables for the stock prices on a future date(Linders, Dhaene, & Schoutens, 2015). The uniform existence and their universal presence in heuristic driven trades have been established in a study who further argues that heuristic driven market participants and informed participants are two disjoint sets(Ormos & Timotity, 2016). Though they operate from the same geography HSI and SSE have very little in common and the movement of the indices also differ, establishing that these two markets are moving towards being more efficient(Ghosh, 2016a). Using SNP 500 stocks data, it has been established that higher the self-similarity exponent in the market transactions, one is likely to find a higher degree of herding behaviour beginning to emerge(Fernández-Martínez, M.; Sánchez-Granero, M. A.; Muñoz Torrecillas, M. J.; McKelvey, 2016). Study conducted using CNX Nifty data relating to pre-2008, to check if there was any evidence of formation of asset price bubble, showed that there were unexplainable deviation and asset price movements in a relatively short time period, within which it was unlikely that the uniform information dissemination would have been possible, resulting in a herding like situation followed by a bubble(Ghosh, 2016b). Power-Law distribution of changes in the stock prices of one segment highlights the possibility of the existence of or beginning of a bubble which is due to herding behaviour of market participants. The study also indicates that detrended Fluctuation Analysis is useful for identifying the beginning of a bubble(Muñoz Torrecillas, Yalamova, & McKelvey, 2016). Ability to predict continuously extremely high returns which are not necessarily well explained is very important from the point of view of financial risk management. Using in-sample and out-sample tests, such bubble formations can be predicted(Jiang et al., 2016).

Citations

Ausloos, M. (2013). Econophysics: Comments on a few Applications, Successes, Methods, & Models. *IIM Kozhikode Society & Management Review*, *2*(July), 101–115. https://doi.org/10.1177/2277975213507832

Ausloos, M., Jovanovic, F., & Schinckus, C. (2016). On the "usual" misunderstandings between econophysics and finance: Some clarifications on modelling approaches and efficient market hypothesis. *International Review of Financial Analysis*, *47*. https://doi.org/10.1016/j.irfa.2016.05.009

Brandouy, O., Delahaye, J. P., & Ma, L. (2015). Estimating the algorithmic complexity of stock markets. *Algorithmic Finance*, *4*(3–4), 159–178.

https://doi.org/10.3233/AF-150052
Cao, L., & Tay, F. E. H. (2001). Financial Forecasting Using Support Vector Machines. *Neural Computing Applications*, *10*(2), 184–192. https://doi.org/10.1007/s005210170010
Chen, B., & Lu, C. (2014). Linear-Time Accurate Lattice Algorithms for Tail Conditional, *3*, 1–78. https://doi.org/10.3233/AF-140034
Da Silva, S., Matsushita, R., & Gleria, I. (2003). International Finance from Macroeconomics to Econophysics. *DeptEconomiaUFRGS–Texto Para Discussão*, *27*, 34.
Daniela Alexandra CRIȘAN. (2015). Journal of information systems & operations management. *Journal of Information Systems & Operations Management*, (178), 482–493.
Didier Sornette. (2003). *Why Markets Crash* (1st ed.). Princeton University Press.
Diego, S. (2010). FIELDS : BEHAVIORAL FINANCE AND ECONOPHYSICS Market Crowd ' s Trading Conditioning and Its Measurement (Previous title is " A Security Price Trading Conditioning Model ") Society for the Advancement of Behavioral Economics Annual Conference , 2010 San Di, 1–38.
Fernández-Martínez, M.; Sánchez-Granero, M. A.; Muñoz Torrecillas, M. J.; McKelvey, B. (2016). A COMPARISON OF THREE HURST EXPONENT APPROACHES TO PREDICT NASCENT BUBBLES IN S&P500 STOCKS Read More: http://www.worldscientific.com/doi/abs/10.1142/S0218348X17500062?journalCode=fractals. *Fractals*, *25*(1). https://doi.org/10.1142/S0218348X17500062
Ghosh, B., & Srinivasan, P. (2015). Detection of sentiment in CNX Nifty–An investigative attempt using probabilistic neural network. *International Journal of Business Quantitative Economics and Applied Management Research*, *1*(12), 1–11.
Ghosh, B. (2016a). Do the Dragons Move Together; Co-integrated and Causality Study Among Chinese Bourses- A Curious Case of Hang Seng and Shanghai Stock Exchange. *Al-Barkaat Journal of Finance and Management*, *8*(2), 1–8. https://doi.org/10.5958/2229-4503.2016.00010.2
Ghosh, B. (2016b). Rational Bubble Testing: An in-depth Study on CNX Nifty. *Asian Journal of Research in Banking and Finance*, *6595800028*(66), 2249–7323. https://doi.org/10.5958/2249-7323.2016.00028.6
Ghosh, B. (2017). Quest for Behavioural Traces the Neural Way: A Study on BSE 100 along with its Oscillators. *Indian Journal of Research in Capital Markets*, *4*(1), 19–25.
Ghosh, B., & Kozarević, 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
Ghosh, B., M.C., K., 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
Ghosh, B., & Srinivasan, P. (2015). Comparative Predictive Modeling on CNX Nifty with Artificial Neural Network Bikramaditya Ghosh Padma Srinivasan. *SDMIMD Journal of Management*, *7*(1), 1–12.

Gusev, M., Kroujiline, D., Govorkov, B., Sharov, S. V., Ushanov, D., & Zhilyaev, M. (2015). Predictable markets? A news-driven model of the stock market. *Algorithmic Finance*, *4*(1–2), 5–51. https://doi.org/10.3233/AF-150042
Hurst, H. (1951). Long term storage capacity of reservoirs. *Trans. Am. Soc. Civ. Eng.*, *6*, 770–799.
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
Jiang, Z.-Q., Wang, G.-J., Canabarro, A., Podobnik, B., Xie, C., Stanley, H. E., & Zhou, W.-X. (2016). Short term prediction of extreme returns based on the recurrence interval analysis.
Jovanovic, F., & Schinckus, C. (2013). ECONOPHYSICS : A NEW CHALLENGE FOR FINANCIAL ECONOMICS ?, *35*(3), 1–35. https://doi.org/10.1017/S1053837213000205
Kempf, A., & Korn, O. (1999). Market depth and order size. *Journal of Financial Markets*, *2*, 29–48. https://doi.org/10.1016/S1386-4181(98)00007-X
Kim, M., & Kim, M. (2014). Group-wise herding behavior in financial markets: An agent-based modeling approach. *PLoS ONE*, *9*(4), 1–7. https://doi.org/10.1371/journal.pone.0093661
Linders, D., Dhaene, J., & Schoutens, W. (2015). Option prices and model-free measurement of implied herd behavior in stock markets. *International Journal of Financial Engineering*, *02*(02), 1550012–35. https://doi.org/10.1142/S2424786315500127
Los, C. A. (2004). Measuring Financial Cash Flow and Term Structure Dynamics. *SSRN Electronic Journal*.
Muñoz Torrecillas, M. J., Yalamova, R., & McKelvey, B. (2016). Identifying the Transition from Efficient-Market to Herding Behavior: Using a Method from Econophysics. *Journal of Behavioral Finance*, *17*(2), 157–182. https://doi.org/10.1080/15427560.2016.1170680
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
Paulo, S., & Schinckus, C. (2013). How Physicists Made Stable Lévy Processes Physically Plausible. https://doi.org/10.1007/s13538-013-0142-1
Physics, J. O. F., Physics, A., & Welfare, S. (2015). The String Theory of Indian Stock Market Nanostructure System -Information Structure, (October).
Racorean, O. (2015). Are financial markets an aspect of quantum world? *Journal of Engineering Science and Technology Review*, *8*(1). https://doi.org/10.25103/jestr.104.04
Sarkissian, J. (2016). Quantum theory of securities price formation in financial markets, 1–38.
Sinha, S., & Chakrabarti, B. K. (2012). Econophysics - An Emerging Discipline. *Economic & Political WEEKLY*, *47*(32).
Staliunas, K. (2003). Bose-Einstein Condensation in Financial Systems. *ArXiv Preprint Cond-Mat/0303271*.
Zahedi, J., & Rounaghi, M. M. (2015). Application of artificial neural network models and principal component analysis method in predicting stock prices on Tehran Stock Exchange. *Physica A: Statistical Mechanics and Its Applications*, *438*(February 2016), 178–187.

https://doi.org/10.1016/j.physa.2015.06.033
Zhang, C., & Huang, L. (2010). 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
Zheng, Z., Qiao, Z., Tenenbaum, J. N., Stanley, H. E., & Li, B. (2014). Predicting market instability: New dynamics between volume and volatility. *ArXiv:1403.5193v1 [q-Fin.ST]*, (1), 1–6.
Zhou, R., Cai, R., & Tong, G. (2013). Applications of entropy in finance: A review. *Entropy*, *15*(11), 4909–4931. https://doi.org/10.3390/e15114909
Zhou, W., & Sornette, D. (2003). Renormalization group analysis of the 2000-2002 anti-bubble in the US S & P 500 index : Explanation of the hierarchy of 5 crashes and prediction. *ArXiv:Physics/0301023v2physics/0301023v2*, (January 2018), 1–30.